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Anti-Immigrant Sentiment and Occupational Context: An Examination of Multilevel Model Estimates When Samples Are Small

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Many who study anti-immigrant sentiment attribute negative attitudes among the native population to objective economic threats that immigrants may pose. In multilevel studies, researchers focus almost exclusively on geographic regions, such as metropolitan areas or countries, as contexts within which to examine the consequences of objective economic threats. Although geographic regions are relevant, it is important to measure competition in other contextual units, such as occupations. Methodological challenges, however, have inhibited the measurement of economic competition and other important concepts in alternative contexts. Small sample sizes within occupations, for example, raise questions about statistical power and estimation. In this paper, the author uses data from the 2004 General Social Survey (GSS) to examine the consequences of small occupation-specific sample sizes for multilevel models predicting the perceived threat of immigrants in the US. The author examines estimates using different groupings within the International Standard Classification of Occupations (ISCO) scheme: 1) 390 detailed occupations, 2) 116 minor groups, 3) 28 sub-major groups and 4) 9 major groups. Results demonstrate that estimates based on a larger number of occupations (i.e., 390 or 116) are generally adequate despite the small occupation-specific sample sizes. Moreover, pooling the data substantially reduces the between-occupation variance, which may lead researchers to conclude that occupations are irrelevant.

Key words: anti-immigrant attitudes; perceived threat; occupations; multilevel modeling

INTRODUCTION

The public reception of immigrants is an enduring area of interest for social scientists (see, for example, Ceobanu and Escandell 2010; Fetzer 2012; Meuleman and Billiet 2012). Scholars often attribute anti-immigrant sentiment to economic competition. Those who compete for jobs with the foreign-born are expected to express greater anti-immigrant sentiment (Berg 2009, 42; Espenshade and Hempstead 1996, 541-42). Scholars often measure labor market competition at multiple levels of analysis. Common individual-level measures of competition include education, income and/or social class. Common contextual measures of competition include the unemployment rate, the relative size of the foreign-born population and/or GDP per capita (see, for example, Meuleman, Davidov and Billiet 2009;Semyonov, Raijman and Gorodzeisky 2006).

In nearly all multilevel studies, geographic regions serve as the higher-level unit of analysis. Contextual indicators of competition are often measured at the country-level in cross-national research and at the metropolitan-level in single country studies. There has been some discussion about which geographic unit of analysis is most appropriate (see Fossett and Kiecolt 1989, 825; Ha 2010, 30; Hjerm 2009, 48; McLaren 2003, 921; Oliver and Mendelberg 2000, 577; Quillian 1995, 592). Few, however, have considered measuring economic competition in other non-geographic contexts, such as occupations (for exceptions, see Mayda 2006; Ortega and Polavieja 2009; Scheve and Slaughter2001).

There are at least three reasons why we should consider occupations as contextual units of analysis in multilevel studies of anti-immigrant sentiment. First, competition within labor market areas (i.e., geographic regions) varies by occupation. A variety of factors, such as skill requirements, training costs, credentialing and demand, limit the competition for jobs in some occupations (see Stolzenberg 1975). As a result, those working in some occupations are less susceptible to economic conditions within labor market areas. Second, labor market competition often occurs between groups of workers, such as immigrants and native workers (Bonacich1972; Hodge and Hodge 1965). Third, the conditions of work impact multiple dimensions of personality including intellectual flexibility (i.e., intellectual performance) and orientation to self and society (e.g., authoritarian-conservativism, standards of morality, trustfulness, self-deprecation, idea conformity, fatalism, anxiety and self-confidence) (Kohn 1990, 52-53; Kohn and Slomczynski 1990, chap. 4).

The neglect of occupations in studies of anti-immigrant sentiment may be a function of concern over small occupation-specific sample sizes. In this paper, I examine perceived threat in the US. Survey respondents are nested within occupations. I estimate the multilevel models separately using four different occupational groupings within the International Standard Classification of Occupations scheme (ISCO-88):390 detailed occupations, 116 minor groups, 28 sub-major groups and 9 major groups. As the number of groups decreases, the group-specific sample sizes increase. Increasing the group-specific sample sizes may lead to a more reliable estimation of occupation-specific parameters (i.e., intercepts and slopes). Grouping cases from different occupations into a smaller number of clusters, however, may obscure important differences between occupations and may be unnecessary. The primary purpose of this paper is to evaluate the adequacy of the estimates under each of the different aggregation/ grouping options in order to provide recommendations for others interested in occupational effects. These results should be of interest to researchers considering occupational effects using secondary data where the number of survey respondents and occupations are out of the control of the researcher.

OCCUPATION AS CONTEXT: METHODOLOGICAL CHALLENGES

The data most commonly used to study attitudes toward immigrants include the European Social Survey (ESS), the International Social Survey Programme (ISSP), the Eurobarometer, the World Values Survey (WVS) and, in the US, the American National Election Studies (ANES) and the General Social Survey (GSS), which participates in the ISSP (see Ceobanu and Escandell 2010 for a discussion of most of these data).These data typically contain responses for between 1,000 and 2,000 people per country. Only the ESS, ISSP and GSS, however, may be suitable for multilevel analyses with individuals nested within occupations. The other data sources do not contain standard occupation codes (e.g., they have an occupation variable with only a dozen or so categories that indicate employment status, industry, supervisory status and/or ownership) and/or they restrict access to the detailed occupation codes.

The ESS, ISSP and GSS data files contain occupation codes for the ISCO-88 scheme. The GSS also contains 1980 US Census occupation codes. The ISCO-88 and 1980 US Census schemes have a maximum number of 390 and 505unique occupation codes, respectively.ISCO-88 is a nested scheme in which 390 detailed occupations or unit groups are nested within 116 minor groups, 28 sub-major groups and 9 major groups (for more information on ISCO-88 see Ganzeboom and Treiman 1996; International Labour Organization 2013).

In a two-level hierarchical model, survey respondents could be viewed as being nested within occupations. Since occupations do not serve as strata within most sampling designs, the occupations represented in the survey data are there by chance. Assuming some type of probability sampling, occupations with more incumbents in the population should have a greater chance of being represented in the survey data and they should be represented in greater numbers. Although not all occupations are likely to be represented in the data, it is clear that the average number of incumbents per occupation will be relatively low. For all three data sources, we would expect to have about seven or eight incumbents per occupation, on average, if the total sample size is 1,500 (per country) and 200 of 390 occupations are represented in the data. There is also likely to be considerable variation in the occupation-specific sample sizes, with some occupations being represented by only a single person.

One obvious challenge to treating occupations as a unit of analysis in a multilevel design, then, is sample size. Although occupations have served as units of analysis in other studies (e.g., studies of wage inequality and occupational segregation), these are often based on micro Census data that contain millions of cases (see, for example Cohen and Huffman 2007; Grodsky and Pager 2001; Kaufman 2002). Treating occupations as units of analysis in studies utilizing survey data is more of a challenge because fewer groups (i.e., occupations) will be present in the data, the group-specific sample sizes will be much smaller and there will be considerable variation in the group-specific sample sizes (i.e., the data are unbalanced).

There are several possibilities for increasing occupation-specific sample sizes in survey-based studies. First, it might be possible to pool several cross-sectional studies. Many items in the GSS, for example, are asked in repeated cross-sectional surveys. Pooling two or three waves of the data would likely increase the number of occupations represented in the data as well as increase the occupation-specific sample sizes. Second, since the ISCO-88 scheme is a nested system, it might be possible to collapse detailed occupations into fewer occupational groupings. Third, some have suggested that resampling procedures (e.g., bootstrapping) may be useful in situations where sample sizes are small (see Roberts and Fan 2004; van der Leeden, Meijer and Busing 2008).

None of these options, however, is without limitation. Measures of perceived group threat, for example, are available in the 1994, 1996, 2000 and 2004 GSS cross-sections. Unfortunately, question wording and the number of response choices vary by year such that only three items are comparable for 1996 and 2004 and two for 1994 and 2000. Additionally, occupation-level variables from other sources (e.g., micro census data) may not be available for each year. When occupations are collapsed into fewer categories, some of the between-occupation variance (e.g., mean differences in the outcome or differences in the slope of a variable)is transferred into within-occupation variance. This may lead to the underestimation of occupational differences and may increase the chances of concluding that occupations do not matter. Care must also be taken when combining occupation-level data (e.g., the percent unemployed) to prepare for the analyses. When combining detailed occupations into fewer categories, the researcher could, for example, compute a simple average or a weighted average based on the relative number of job incumbents. Finally, Hox (2004) concludes: "the bootstrap is probably not the best approach when the problem is a small sample size. When the problem is violations of assumptions, or establishing bias-corrected estimates and valid confidence intervals for variance components, the bootstrap appears to be a viable alternative…" (204).

In sum, occupations are a relevant unit of analysis in studies of anti-immigrant sentiment. While it may be preferable to focus on detailed occupations, small occupation-specific sample sizes may impact our ability to estimate a variety of submodels within multilevel modeling. Although alternatives may exist, these approaches also face limitations and they may not be necessary. The purpose of this paper is to explore this last issue empirically. In this paper, I treat respondents as being nested within occupations. The study focuses on perceived group threat, education and projected employment growth. I estimate three common multilevel models that will allow me to determine if perceived group threat and the relationship between threat and education vary across occupations and, if they do, to model this variation as a function of projected employment growth. I estimate these models using four different levels of nesting within the ISCO-88 scheme: 9 major groups, 28 sub-major groups, 116 minor groups and 390 unit groups. The primary question guiding the analysis is: which ISCO grouping options are acceptable for each multilevel submodel? The goal is to provide a workable strategy for those interested in using multilevel modeling and survey-based studies to explore occupational differences in intercepts and slopes.

METHODOLOGY

Data

The individual-level data are from the 2004 General Social Survey (Davis and Smith, 2004). The response and refusal rates are 0.704 and 0.225, respectively (see Appendix Table A.6 in the GSS codebook). The original sample size for these data is 2,812. 1,215 of these respondents completed the International Social Survey Program (ISSP) module, National Identity II, which contains an extended set of questions on attitudes toward immigrants and immigration policy. I limit all analyses to the 1,169 respondents who completed this module and are American citizens. The final sample size is 1,113. I lose 56 of the 1,169 cases because they lack valid data on perceived group threat and/or they lack a valid occupation code. I use the weight *WTSSNR* for all analyses (see Appendix A in the GSS codebook for a description of the weight). In sum, I include only those respondents who are US citizens (born in the US or naturalized) and who were working in the week before they were surveyed or had ever worked for as long as one year.

The dependent variable, perceived group threat, is a standardized index composed of four items (each has five response choices ranging from “disagree strongly” to “agree strongly”): immigrants take jobs away, immigrants are good for the economy, immigrants improve society by bringing in new ideas and cultures and immigrants increase crime rates. Exploratory factor analysis results indicate that an index composed of these four items is reliable (see Appendix Table A1). I recoded each item such that a high score indicates threat. I computed the mean value across the items and standardized the result(minimum=-2.3, maximum=2.7, mean=0.0). I allow missing data on up to three items to maximize the sample size (this allows me to retain 51 cases, which are mostly missing only one response).

The independent variables are years of education (minimum=0, maximum=20, mean=13.9) and the projected rate of employment growth (minimum=-45.5%, maximum=49.6%, mean=9.7%). Education is perhaps the most consistent predictor of anti-immigrant sentiment in single-country studies and in cross-national research (Ceobanu and Escandell 2010, 319). Research suggests that projected employment growth may be the most important occupation-level predictor of perceived group threat (Kunovich 2013).I limit the models to these two variables in order to limit the size of the tables and because the purpose of this paper is to examine the impact of small occupation-specific sample sizes on estimation rather than to develop a comprehensive model of perceived group threat. The projected growth variable is measured at the occupation level and it is from the 2004-2014 Bureau of Labor Statistics (BLS) Employment Projection Data (http://www.bls.gov/opub/mlr/mlrhome.htm in the Appendix of Hecker, November 2005). It is equal to the projected change in the percent employed from 2004 to 2014 and measures projected employment growth that is unrelated to the supply of workers.

Analytic Technique

I use multilevel modeling software, HLM 7.0, to estimate all models. The correlation between occupation-specific frequencies from the 2004 GSS, which utilizes probability sampling, and the total number of people employed in each occupation (from Bureau of Labor Statistics estimates) is 0.70. It therefore seems reasonable to assume that the occupations represented in the data constitute a probability sample.

Two occupational classifications are available in the 2004 GSS data: 1980 US Census occupation codes and ISCO-88. I rely on the ISCO-88 classification because of its hierarchical structure. ISCO-88 is composed of 390 unit groups (i.e., detailed occupations) and three additional groupings: 116 minor groups, 28 sub-major groups and 9 major groups. This structure allows me to estimate the HLM submodels four times – that is, with individuals nested within the detailed occupations, the minor groups, the sub-major groups, and the major groups. As the number of occupational groups decreases (i.e., from the detailed occupations to the major groups), the number of job incumbents per group increases. I can examine the results for each of these options to evaluate the impact of occupation-specific sample sizes on estimation.

It should be noted that it is not possible to directly compare the results for a single model across the four different levels of nesting. This is due to the fact that different respondents are combined within different groups to estimate the four sets of models. The "legislators and senior officials" category, for example, is treated as a separate occupational category for all models based on the ISCO sub-major groups, but it is combined with "corporate managers" and "general managers" for all models based on the ISCO major groups (see Table 1). Moreover, the "corporate managers" sub-major category combines six more detailed occupational groups, which are treated as unique in all models based on the ISCO unit groups. Changes in the estimates could, therefore, be due to differences in the composition of the groups (i.e., which specific people are combined in the group) or in the reliability of estimates (i.e., from having fewer or more people combined in the group). Despite this, it is possible to examine the adequacy of the models separately by ISCO grouping.

Table 1 Perceived Group Threat: Means by ISCO-88 Major and Sub-Major Groups

ISCO-88 Major and Sub-Major Groups	Nested Occupations	Mean (z score)	N	Mean (z score)	N
1 Legislators senior official and managers	8	-0.193	188		
1100 Legislators and senior officials	1			-0.418	18
1200 Corporate managers	6			-0.214	132
1300 General managers	1			-0.011	38
2 Professionals	36	-0.432	232		
2100 Physical, mathematical, engineering science prof.	11			-0.487	47
2200 Life science and health professionals	6			-0.388	26
2300 Teaching professionals	6			-0.451	76
2400 Other professionals	13			-0.398	83
3 Technicians and associate professionals	28	-0.044	131		
3100 Physical and engineering science associate prof.	8			-0.083	21
3200 Life science and health associate professionals	6			0.081	31

3300 Teaching Associate Professionals	1			0.057	10
3400 Other associate professionals	13			-0.104	69
4 Clerks	16	0.085	157		
4100 Office clerks	11			0.038	116
4200 Customer service clerks	5			0.218	41
5 Service workers and shop and market sales workers	15	0.187	134		
5100 Personal and protective service workers	13			0.115	107
5200 Salespersons, models, and demonstrators	2			0.473	27
6 Skilled agricultural and fishery workers	3	0.989	9		
6100 Market-oriented skilled ag. and fishery workers	3			0.989	9
6200 Subsistence agricultural and fishery workers	0		0		0
7 Craft and trade workers	26	0.371	98		
7100 Extraction and building trade workers	7			0.441	33
7200 Metal, machinery, etc. trade workers	10			0.308	41
7300 Precision, handicraft, printing, etc. trade workers	3			0.591	3
7400 Other craft, etc. trade workers	4			0.283	8
7500 Skilled workers NSF	2			0.393	13
8 Plant and machine operators and assemblers	19	0.496	90		
8100 Stationary-plant etc. operators	6			0.830	9
8200 Machine operators and assemblers	7			0.657	42
8300 Drivers and mobile-plant operators	6			0.246	39
9 Elementary occupations	12	0.158	74		
9100 Sales and service elementary occupations	6			0.099	34
9200 Agricultural, fishery, etc. laborers	1			0.598	14
9300 Laborers in mining, construction, man., transport	5			-0.001	26
Total		-0.002	1113	-0.002	1113
Eta squared		0.093		0.107	
F		14.161*		5.020*	
d.f. (ISCO 9)		8, 1104		26, 1086	

* p < .05.

Existing simulation studies demonstrate the impact of sample size on estimation and power within multilevel modeling (for reviews, see Hox 2004, 173-94; Kreft and de Leeuw 1998, 119-26; Raudenbush and Bryk 2002, 280-84; Snijders and Bosker 1999, 140-54). These often address cost issues and typically assume that the question is whether or not to sample additional level-2 groups, to sample additional level-1 cases per group, or to do both of these. In other words, the focus is not on what happens when disparate groups are combined. These reviews do, however, provide guidance on what to expect when sample sizes are small – this is discussed in detail below.

HLM Submodels

I estimate three common HLM submodels: the One-way ANOVA with random effects model, the random-coefficient regression model and the intercepts- and slopes-as-outcomes model. Multilevel models can be represented by separate level 1 and level 2 models as well as a more complex combined model; I present both for each submodel below.

The purpose of the one way ANOVA with random effects model is to determine if perceived group threat varies across occupations (i.e., if the occupation means/intercepts are different in the population). The model is defined as:

Level 1: $$Y_{ij} = \beta_{0j} + r_{ij} \qquad (1)$$

Level 2: $$\beta_{0j} = \gamma_{00} + u_{0j} \qquad (2)$$

Combined: $$Y_{ij} = \gamma_{00} + u_{0j} + r_{ij} \qquad (3)$$

where Y_{ij} is the observed perceived group threat score for person i in occupation j; β_{0j} is the mean perceived group threat score for occupation j (it is random); γ_{00} is the grand mean perceived group threat score across all people and occupations (it is fixed); u_{0j} is the difference between the grand mean perceived group threat score and the group mean for occupation j; and r_{ij} is the deviation in perceived group threat from person i in occupation j from the group mean in occupation j. u_{0j} and r_{ij} have variance; these are labeled as τ_{00} and σ^2, respectively. The group and person-level variance components for this submodel (i.e., τ_{00} and σ^2)reflect the total variation in perceived group threat between and within groups because the model contains no independent variables. The intraclass correlation indicates the proportion of variation in perceived group threat that is between occupations. It is defined as:

$$ICC = \frac{\tau_{00}}{(\tau_{00} + \sigma^2)} \cdot \quad (4)$$

The purpose of the random-coefficient regression model is to determine if the education slope varies across occupations. It is defined as:

Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{X}_{.j}) + r_{ij}$ (5)

Level 2: $\beta_{0j} = \gamma_{00} + u_{0j}$ (6)

$\beta_{1j} = \gamma_{10} + u_{1j}$

Combined: $Y_{ij} = \gamma_{00} + u_{0j} + \gamma_{10}(X_{ij} - \bar{X}_{.j}) + u_{1j}(X_{ij} - \bar{X}_{.j}) + r_{ij}$ (7)

where $(X_{ij} - \bar{X}_{.j})$ is education for person i and occupation j centered around the group mean for occupation j; β_{1j} is the education slope for occupation j (it is random); γ_{10} is the average education slope across all occupations (it is fixed); and u_{1j} is the difference between the education slope for group j and the average slope (i.e., γ_{10}). u_{0j}, u_{1j} and r_{ij} have variance; these are labeled τ_{00}, τ_{11}, and σ^2, respectively. u_{0j} and u_{1j} also have a covariance, which is labeled τ_{01} or τ_{10}. The person-level variance component (r_{ij}) now indicates residual variation in perceived group threat because a person-level variable has been added to the model (i.e., education). The group-level variance components reflect the total variation in the group means for perceived group threat and the group slopes for education because education is group-mean centered and because no other variables have been entered to predict the variation in the intercepts and slopes.

The purpose of the intercepts- and slopes-as-outcomes model is to predict variation in perceived group threat and in the education slope across occupations. It is defined as:

Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - \bar{X}_{.j}) + r_{ij}$ (8)

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$ (9)

$\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j}$

Combined: $Y_{ij} = \gamma_{00} + \gamma_{01}W_j + u_{0j} + \gamma_{10}(X_{ij} - \bar{X}_{.j}) + \gamma_{11}W_j(X_{ij} - \bar{X}_{.j}) +$
$u_{1j}(X_{ij} - \bar{X}_{.j}) + r_{ij}$ (10)

where W_j is an occupation-level variable (i.e., projected employment growth); γ_{01} is the slope for W_j (it is fixed); and γ_{11} is the slope that describes the cross-level interaction between projected employment growth and education (it is fixed). All of the variance components now indicate residual variation after controlling for the person and occupation-level independent variables.

Estimation in HLM

Fixed Effects

Estimates for fixed effects – for example, the grand mean perceived threat score (γ_{00}), the average education slope (γ_{10}), the projected employment growth slope (γ_{01})and the slope for the cross-level interaction (γ_{11}) – are precision weighted averages (see Raudenbush and Bryk 2002, 38-45). Each occupation contributes to the overall result, but this contribution is weighted by the precision of the estimate for each occupation. Precision is determined by the occupation-specific sample size. Occupations with larger sample sizes contribute more to the estimation of the fixed effects than occupations with smaller sample sizes. Since occupations with more job incumbents in the population are more likely to be included in the survey data, more common occupations play a more important role in determining the estimates than less common occupations.

A number of existing texts discuss estimation and statistical power in multilevel modeling. They also summarize results from simulation studies with different sample sizes at level 1 and level 2 (see, for example, Hox 2002, 173196; Raudenbush and Bryk 2002, 280-84). Raudenbush and Bryk (2002) state that the estimates of fixed effects are unbiased with any sample size, but that standard error estimates are downwardly biased with small samples (p. 281). Hox (2002), citing a simulation study, states that the slight downward bias in standard errors occurs only when the number of groups is less than 50 (p. 173). With respect to power, the total sample size (i.e., the total number of individuals) matters most for the estimation of individual-level slope coefficients while the number of groups matters most for the estimation of group-level slope coefficients, including cross-level interactions (see Hox 2002,173–74). Despite this, "[f]or accuracy and high power a large number of groups appears more important than a large number of individuals per group" (Hox 2002,174).

In sum, existing research suggests that it may be better to maximize the number of occupations. Also, we might anticipate downwardly biased standard errors in models based on the major and sub-major groups, which contain fewer than 50 occupational groups.

Random Effects

Estimates for random effects – for example, the occupation-specific perceived group threat means/intercepts(β_{0j}) and the occupation-specific education slopes (β_{1j}) – are based on empirical Bayes estimation (see Raudenbush and Bryk 2002, 45–51). Two pieces of information are used to estimate the group means for each occupation: the overall grand mean across all occupations (γ_{00} in equation 2, which is a precision weighted average) andthe occupation-specific group means ($\bar{Y}_{.j}$). HLM software uses both of these to generate the estimate: when the sample size within an occupation is large, reliability in that occupation (λ_j in equation 11) is high and greater weight is given to the occupation-specific group mean ($\bar{Y}_{.j}$); when the sample size within an occupation is small, reliability within that occupation (λ_j) is small and greater weight is given to the overall grand mean (γ_{00}).

$$(\lambda_j) = \frac{\tau_{00}}{(\tau_{00} + \frac{\sigma^2}{n_j})} \qquad (11)$$

$$(\lambda) = \sum \lambda_j / J\,. \qquad (12)$$

$$\beta_{1j}^{EB} = \lambda_j \bar{Y}_{.j} + (1 - \lambda_j)\,\gamma_{00} \qquad (13)$$

In this way, HLM provides a conservative estimate for each occupation that controls for differences in the sample sizes across occupations (it is referred to as an empirical Bayes estimate and also as a "shrinkage estimator"; see Raudenbush and Bryk 2002, 45–51). Empirical Bayes estimation for a slope occurs in the same way and is based on the average slope (γ_{10}) and group-specific slope (β_{1j}).

Small occupation-specific samples thus impact reliabilities and the estimates of the occupation means and slopes. Raudenbush and Bryk (2002) suggest that random coefficients should be treated as fixed or non-randomly varying when the reliability (equation 12) for a random level-1 coefficient drops below 0.05 (see pp. 125 and 257).

Variance Components

Estimates of the variance components (u_{0j}, $u_{1j}$and r_{ij}) are based on full maximum likelihood estimation. The variance components describe how much of the variance is within and between groups. HLM uses a chi-squared test to determine if the between-group variation is significant. Raudenbush and Bryk (2002) state that the estimation of the within-group variance is "quite accurate in most applications. If the within group variance is assumed equal in every unit, the precision of its estimation will depend on the total sample size" (283). Regarding the estimate of the between-group variance, they state: “the accuracy of estimation depends on the number of level-2 units” (283). Hox (2002) states that these variance components are sometimes underestimated (see p. 174). Simulation studies cited by Hox, show that the underestimation occurs when the number of groups is small, although there is disagreement about the minimum group size (6-12 or 30 groups with restricted maximum likelihood estimation, 48 groups with full maximum likelihood).

In sum, occupation-specific sample sizes should not negatively influence the estimation of the variance components. We may, however, see differences in the variance estimates across ISCO groupings. In particular, we should look for smaller between-group variance estimates in the analyses based on the major and sub-major groups.

Summary

It is generally preferable to maximize the number of groups. Collapsing detailed occupations into fewer categories will convert between-group variability into within-group variability, which may lead us to believe that there is less between-group variation than there really is. Also, the between-group variance component is underestimated when the number of groups is less than 48 (assuming full maximum likelihood estimation).Finally, the standard errors for occupation-level fixed effects are unbiased when the number of groups is greater than 50. Maximizing the number of occupations, though, must be done within the confines of ensuring that the reliability coefficients for random intercepts and slopes exceed 0.05. If the reliability coefficients are too low, the empirical Bayes shrinkage estimator will bias the estimates toward the grand mean/average slope and we may conclude that there is less between-group variation than there really is.

RESULTS

Information on occupation-specific sample sizes by ISCO-88 grouping is presented in Table 2. The number of job incumbents in the population, sampling, and the overall sample size limit the number of occupations for some ISCO groupings: 9 of 9 major groups, 27 of 28sub-major groups, 89 of 116 minor groups and 163 of 390 unit groups are represented in the data. The occupation-specific sample sizes are smaller when more detailed groupings are used – for example, the mean number of job incumbents is 41.2 for the sub-major groups and 6.8 for the unit groups. Perhaps more distressing than the mean number of incumbents for the unit group option is that the mode for the minor and unit groupings is 1 job incumbent. Moreover, 27.0 and 39.9 percent of the occupations within the minor and unit groupings contain fewer than three job incumbents. Nevertheless, it is possible to generate estimates with small occupation-specific sample sizes. Tabachnick and

Fidell (2007) state: "group sizes may be as small as one, as long as other groups are larger…Simulation studies show that power is greater with more groups (second-level units) and fewer cases per group (first-level units) than the converse, although more of both leads to increased power" (788). The consequences of these small occupation-specific sample sizes will be explored for each submodel below.

Table 2 ISCO-88: Group-specific Sample Sizes in the 2004 GSS

	ISCO-88			
	9 Major Groups	28 Sub-Major Groups	116 Minor Groups	390 Unit Groups
Groups represented in the data	9	27	89	163
Group sample size: Mean	123.7	41.2	12.5	6.8
Group sample size: Median	131.0	33.0	8.0	4.0
Group sample size: Mode	- [a]	- [a]	1	1
Minimum group sample size	9	3	1	1
Maximum group sample size	232	132	116	115
Percent with less than three cases	0.0	0.0	27.0	39.9

a Multiple modes exist.

One Way ANOVA with Random Effects

The primary purpose of the one way ANOVA with random effects model is to determine how much of the variation in perceived group threat is between and within occupations. If all of the variation is within occupations, then there is no need to proceed with multilevel modeling. Results for this model are listed in Table 3. Only one fixed effect is estimated for this model, the grand mean perceived group threat (γ_{00}). This model contains two random effects: the individual-level random effect and the occupation-level random effect, which allows for the estimation of the occupation-specific intercepts.

Although it is possible to test hypotheses about the fixed effect from this submodel (e.g., the population grand mean is equal to zero), this is not of interest in the current analysis.

The most important questions for each ISCO grouping in this model are: 1) does the level of perceived group threat vary across occupations and 2) are the estimates acceptable? The answer to the first question is determined by the variance components (τ_{00} and σ^2) and the associated chi-squared test. The null hypothesis for the chi-squared test is that the means are equivalent across groups in the population. The results in Table 3 indicate that the null hypothesis should be rejected for all four ISCO groupings. The observed chi-squared values exceed the critical chi-squared values for all models (alpha=0.05). The proportion of between-group variance is larger for more detailed occupational groupings: 0.106, 0.107, 0.116 and 0.121 for the major, sub-major, minor and unit groups. This is due to the averaging of values when occupations are combined into fewer groups and can be seen by examining the group mean for the "Legislators, senior officials, and managers" category compared to the group means for the three more detailed occupations within it in Table 1.Some of the between-group variation is transformed into within-group variation when more detailed groups are combined.

Table 3 Perceived Group Threat in the U.S. (2004): One-way ANOVA with Random Effects Models (HLM Estimates)

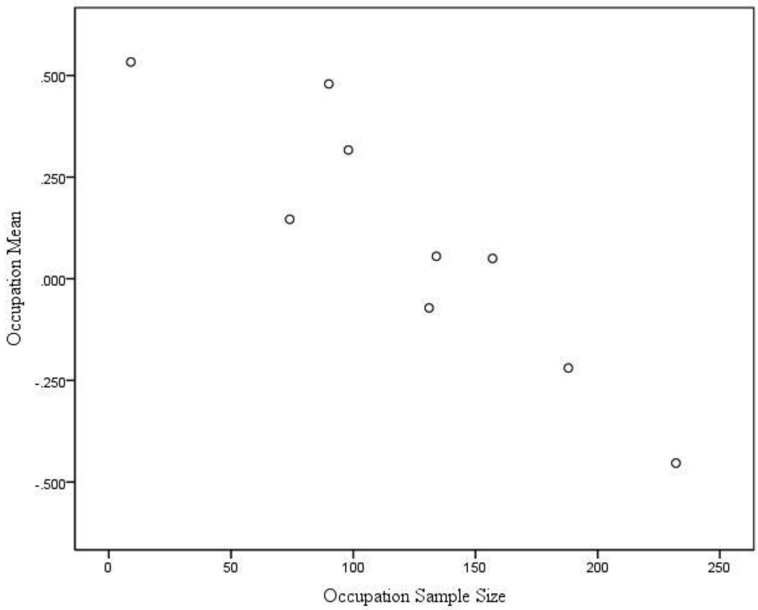
		Variance component	Intra-class correlation	d.f.	χ^2	Intercept (γ_{00})	Standard error	Reliability
ISCO 9	Occupation-level (τ_{00})	0.10325	0.106	8	138.6*	0.082	0.115	0.886
	Individual-level (σ^2)	0.87387						
ISCO 28	Occupation-level (τ_{00})	0.10463	0.107	26	149.9*	0.057	0.074	0.738
	Individual-level (σ^2)	0.87276						
ISCO 116	Occupation-level (τ_{00})	0.11399	0.116	88	208.1*	-0.011	0.055	0.467
	Individual-level (σ^2)	0.86816						
ISCO 390	Occupation-level (τ_{00})	0.11780	0.121	162	296.4*	-0.025	0.048	0.356
	Individual-level (σ^2)	0.85787						

* p < .05

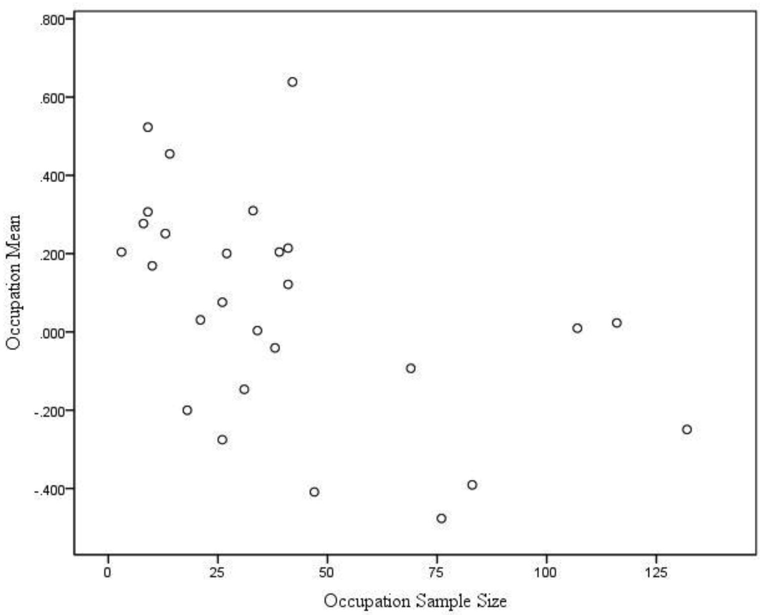
The scatter plots in Figure 1 are also illustrative of what occurs as one moves from the more general to the more detailed occupational groupings. First, as one moves to more detailed occupational groupings, the group-specific sample sizes decrease, which leads to the shifting of the dots (i.e., occupations) to the left on the x-axis. Second, more detailed occupational groups allow for greater variability in the estimates of the means, which leads to the spreading out of the dots (i.e., occupations) on the y-axis. Notice, for example, that the range of values on the y-axis is smallest for the major groups (i.e., ISCO 9). This increased variability, however, is offset by the conservative approach used in empirical Bayes estimation. Under this approach, low reliabilities for occupations with few job incumbents force group-specific estimates toward the middle (i.e., 0). This pattern (shrinkage) is most pronounced for the occupational groups with one incumbent.

Figure 1 Perceived Group Threat: Empirical Bayes Estimates for the Occupation Means (HLM Estimates)

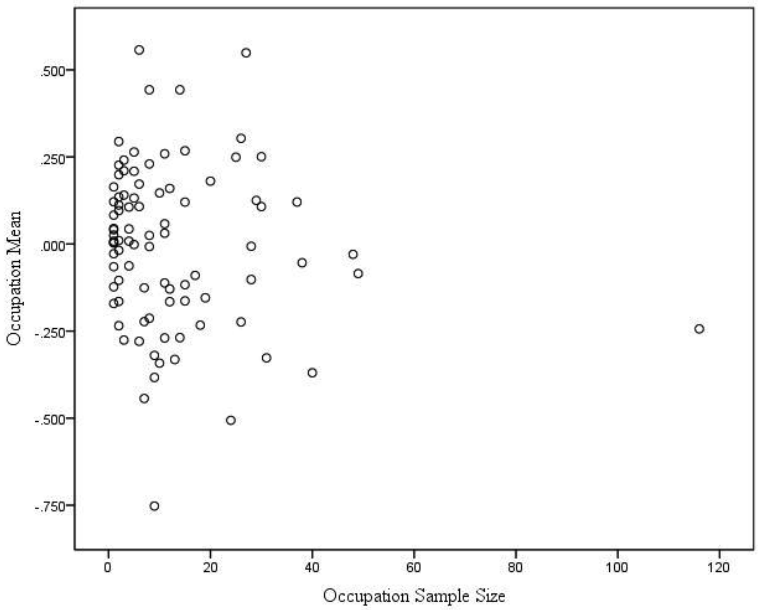
ISCO 9 (N=9)



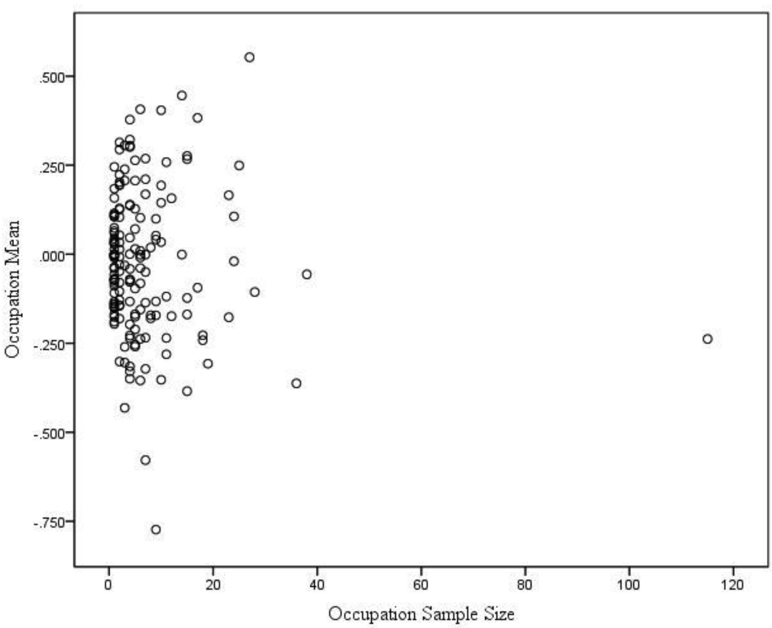
ISCO 28 (N=27)



ISCO 116 (N=89)



ISCO 390 (N=163)



For which grouping option are the estimates best? For the one-way ANOVA model, it would be appropriate to use either the minor groups or the unit groups (i.e., ISCO 116 or 390).Both of these groupings contain data for more than 48 groups so the estimates of the standard errors for the occupation-level fixed effects and the estimates of the between-group variance components should be unbiased. These more detailed groupings also permit greater variability in the occupation means. Finally, despite the small occupation-specific sample sizes, the reliability coefficients (0.467 and 0.356) exceed the minimum threshold of 0.05.

Random-coefficient Regression Model

Results for the random-coefficient regression model are listed in Table 4. This model contains two fixed effects: the grand mean perceived group threat and the average education slope. This model contains three random effects: the individual-level variance component and two occupation-level variance components (one for the occupation-specific intercepts and one for the occupation-specific slopes). The primary purpose of this model is to evaluate whether or not the relationship between perceived group threat and education varies across occupations.

Table 4 Perceived Group Threat in the U.S. (2004): Random Coefficient Regression Models (HLM Estimates)

		Variance component	d.f.	χ^2	Coefficient (γ)	Standard error	Reliability
ISCO 9	Education Slope (τ_{11})	0.00071	8	11.2	-0.074*	0.016	0.307
	Occupation-level (τ_{00})	0.09767	8	145.3*	0.121	0.112	0.887
	Individual-level (σ^2)	0.80961					
ISCO 28	Education Slope (τ_{11})	0.00072	26	28.4	-0.077*	0.015	0.124
	Occupation-level (τ_{00})	0.10122	26	156.4*	0.097	0.073	0.743
	Individual-level (σ^2)	0.81019					
ISCO 116	Education Slope (τ_{11})	0.00165	75	109.0*	-0.079*	0.015	0.092
	Occupation-level (τ_{00})	0.11087	75	201.3*	0.034	0.054	0.530
	Individual-level (σ^2)	0.80585					
ISCO 390	Education Slope (τ_{11})	0.00103	116	143.2*	-0.079*	0.016	0.038
	Occupation-level (τ_{00})	0.11877	116	247.5*	0.021	0.048	0.455
	Individual-level (σ^2)	0.80038					

* p < .05

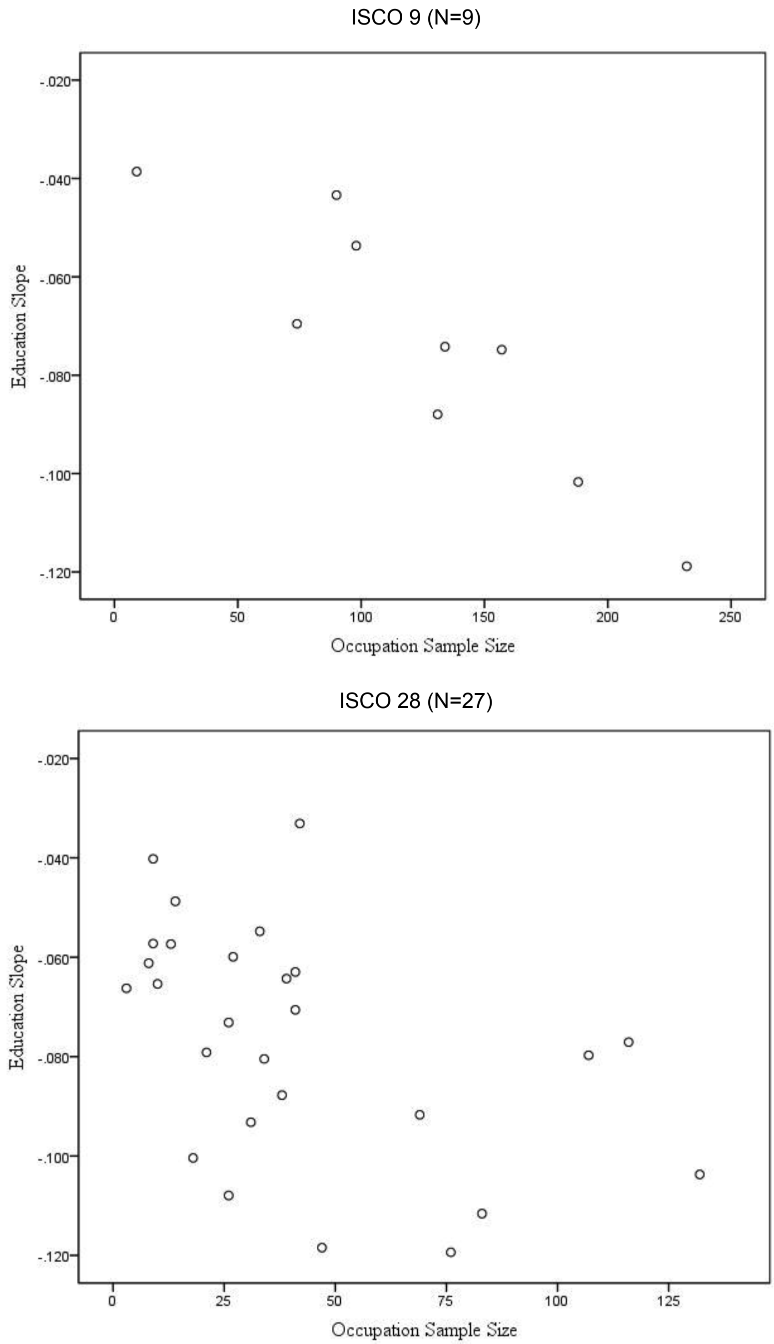
Regardless of the ISCO grouping, one would conclude that, on average, those with more education express less threat. The average slopes and the corresponding standard errors are quite similar across the ISCO groupings. Also, all four ISCO groupings continue to suggest that perceived group threat varies across occupations. It should be noted, however, that no variables have been entered to account for between-group variation in the intercepts. Education cannot explain any of the between-group variation in the intercepts because it is group-mean centered. Group-mean centering is used here because it provides a better estimate of the variance of the slopes (see Enders and Tofighi 2007, 128; Raudenbush and Bryk 2002, 143).Finally, and most importantly, the results indicate that the conclusion about variability in the education slope depends on the ISCO grouping. Based on the associated chi-squared tests, variation in the slope is only significant for the ISCO minor and unit groups (i.e., ISCO 116 and 390).

For which grouping option are the estimates best? Results suggest that the optimal ISCO grouping for this submodel is the minor group (i.e., ISCO 116). The small number of occupational groups in the major and sub-major groupings (i.e., ISCO 9 and 28) lead to an underestimation of the between-group variance component. The chi-squared tests from both of these groupings would lead the researcher to conclude that the slopes do not vary across occupations in the population. A different conclusion would be drawn when using the minor and unit groups (i.e., ISCO 116 and 390). Both of these groupings contain a sufficient number of groups such that the between-group variance in the slopes is not underestimated. The reliability coefficient for the ISCO 390 model, however, fails to reach the suggested minimum of 0.05. This is not unexpected as Raudenbush and Bryk indicate that regression slopes are not estimated as reliably as intercepts (p. 79). This is due to the fact the occupation-specific slopes depend on the occupation-specific sample sizes, which are small, and on variability in education within the occupations, which is likely to be low.

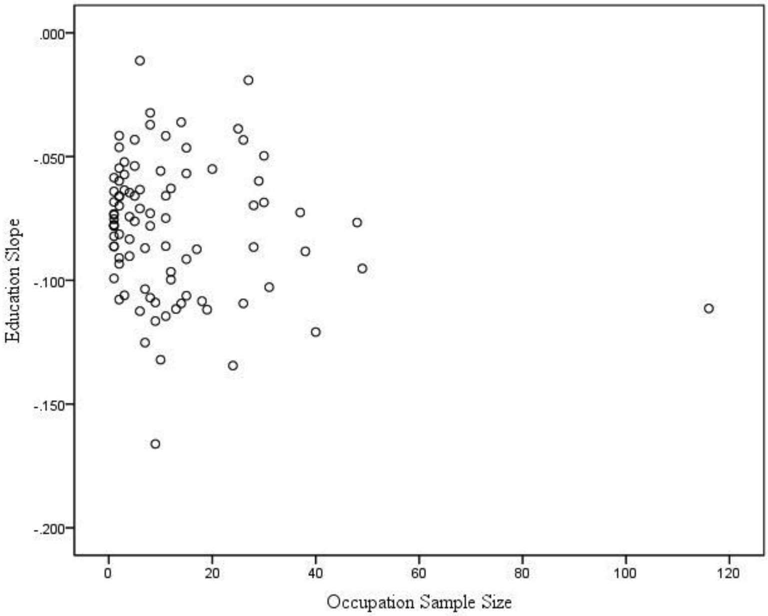
A close inspection of the between-group variance component for the education slope in the minor and unit groupings (i.e., ISCO 116 and 390) indicates that the low reliability under unit grouping results in a lower estimated variance. The empirical Bayes estimator provides occupation-specific estimates that are weighted more heavily toward the average slope across all occupations due to low reliability (0.038).This shrinkage is also evident in Figure 2 – there is a tight clustering on the y-axis of occupations with small sample sizes.

In sum, the best grouping option for this HLM submodel is the minor group (i.e., ISCO 116). It contains a sufficient number of groups to estimate the fixed effects and their standard errors as well as the between-group variance in the intercepts and slopes. It also has sufficiently large occupation-specific sample sizes to reliably estimate the occupation-specific slopes.

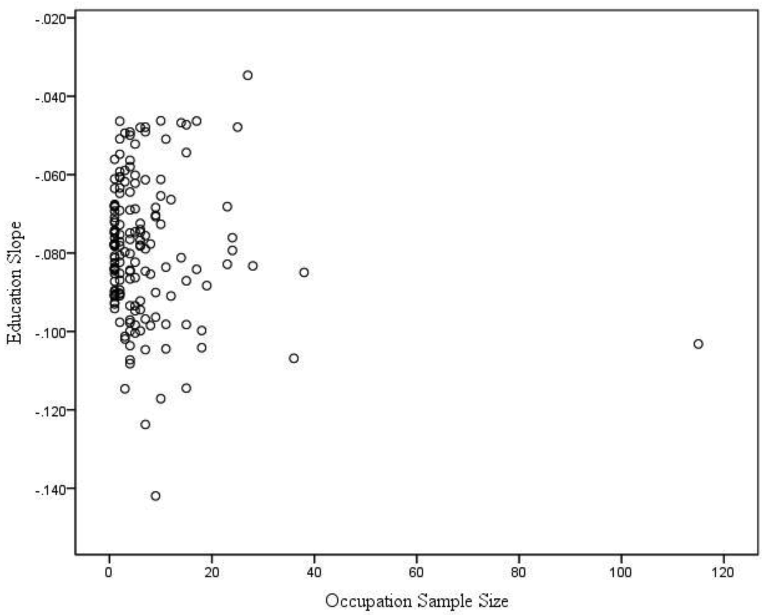
Figure 2 Perceived Group Threat: Empirical Bayes Estimates for the Education Slopes (HLM Estimates)



ISCO 116 (N=76)



ISCO 390 (N=116)



Intercepts and Slopes as Outcomes Model

The purpose of the intercepts and slopes as outcomes model is to explain differences across occupations in the level of perceived group threat and in the relationship between perceived group threat and education. The model contains four fixed effects: the grand mean perceived group threat, the average education slope and the two projected employment growth slopes that explain variation in the intercepts and slopes. The model contains three random effects: the individual-level variance component and two occupation-level variance components (one for the occupation-specific intercepts and one for the occupation-specific slopes). Results from this model are presented in Table 5.

Table 5 Perceived Group Threat in the U.S. (2004): Intercepts and Slopes as Outcomes Models (HLM Estimates)

		Variance component	d.f.	χ^2	Coefficient (γ)	Standard error	Reliability
ISCO 9	Education Slope (τ_{11})	0.00077	7	11.2	-0.075*	0.017	0.325
	Projected Growth				0.000	0.002	
	Occupation-level (τ_{00})	0.08796	7	132.1*	0.117	0.107	0.879
	Projected Growth				-0.008	0.012	
	Individual-level (σ^2)	0.80967					
ISCO 28	Education Slope (τ_{11})	0.00077	25	28.3	-0.076*	0.015	0.131
	Projected Growth				0.000	0.002	
	Occupation-level (τ_{00})	0.08424	25	137.2*	0.095	0.068	0.712
	Projected Growth				-0.012	0.007	
	Individual-level (σ^2)	0.80971					
ISCO 116	Education Slope (τ_{11})	0.00112	74	107.1*	-0.069*	0.016	0.068
	Projected Growth				-0.004*	0.002	
	Occupation-level (τ_{00})	0.08655	74	195.4*	0.068	0.052	0.481
	Projected Growth				-0.016*	0.004	
	Individual-level (σ^2)	0.79878					
ISCO 390	Education Slope (τ_{11})	0.00025	115	140.4	-0.068*	0.016	0.010
	Projected Growth				-0.003*	0.002	
	Occupation-level (τ_{00})	0.09361	115	220.8*	0.051	0.046	0.407
	Projected Growth				-0.017*	0.004	
	Individual-level (σ^2)	0.79305					

* p < .05

The results from Table 5 are similar to those from Table 4. The mean level of perceived group threat varies across occupations regardless of the ISCO grouping choice. Those with more education express less threat, on average, regardless of the ISCO grouping choice. Finally, variance in the education slope is not significant for the major and sub-major groupings.

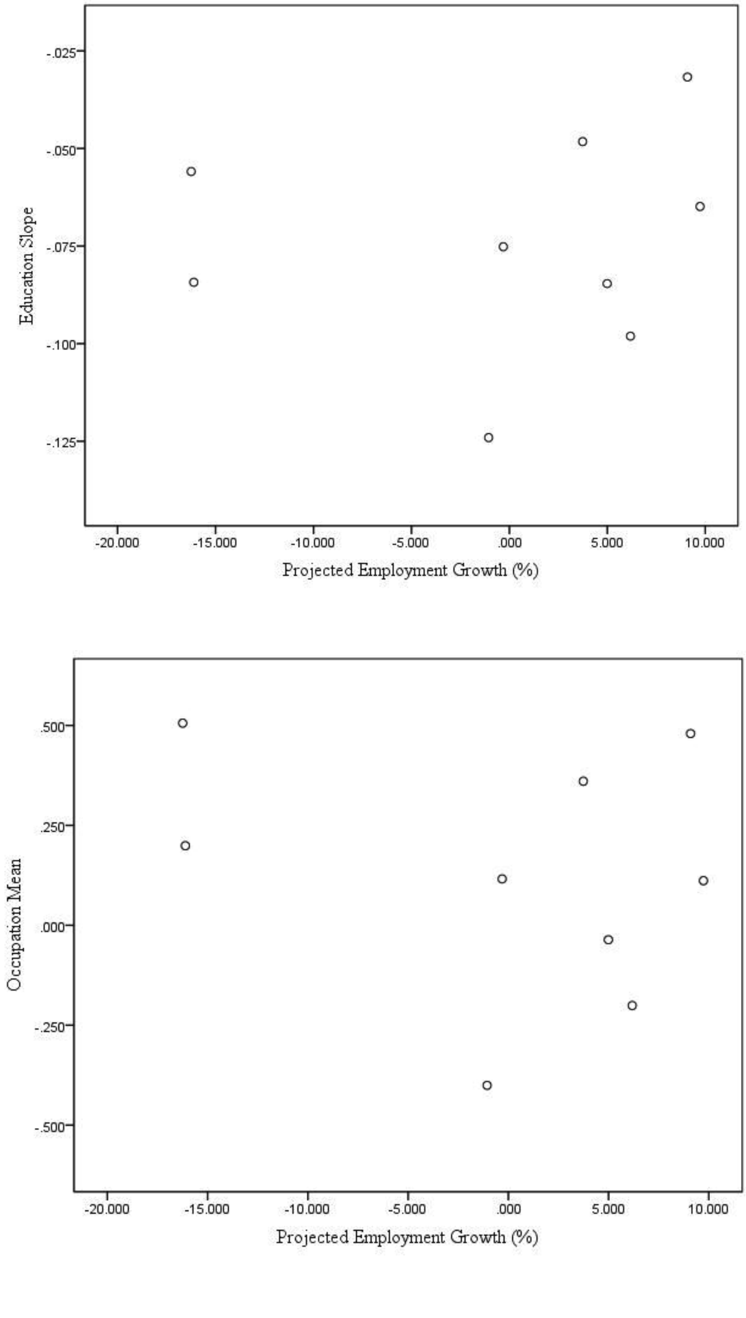
Projected employment growth is an independent variable at the occupation level in these models and is intended to predict variation in both the intercepts and slopes. The results suggest that there is a cross-level interaction between projected employment growth and education, but only under the minor and unit group options. Due to the underestimation of the variance of the slopes across occupations and also perhaps to the aggregation of the projected employment growth variable, it is not significant for the major and sub-major groupings. For the other groupings, however, each one percent increase in the projected rate of employment growth makes the education slope more negative. In other words, those with more education express less threat and this negative slope is even more negative for those working in occupations with greater projected growth. Conversely, education does not reduce threat as much for those working in occupations with greater projected employment decline. The insignificance of the variation of the slopes in the unit group model suggests that projected employment growth explains all of the occupational differences in the effect of education.

The results for projected employment growth are similar when predicting occupational differences in the intercepts. Perceived group threat is lower for those working in occupations with greater projected growth. This is only true, however, for the minor and unit groupings. The relationship between perceived group threat and projected employment growth and the cross-level interaction between projected employment growth and education are depicted in Figure 3.

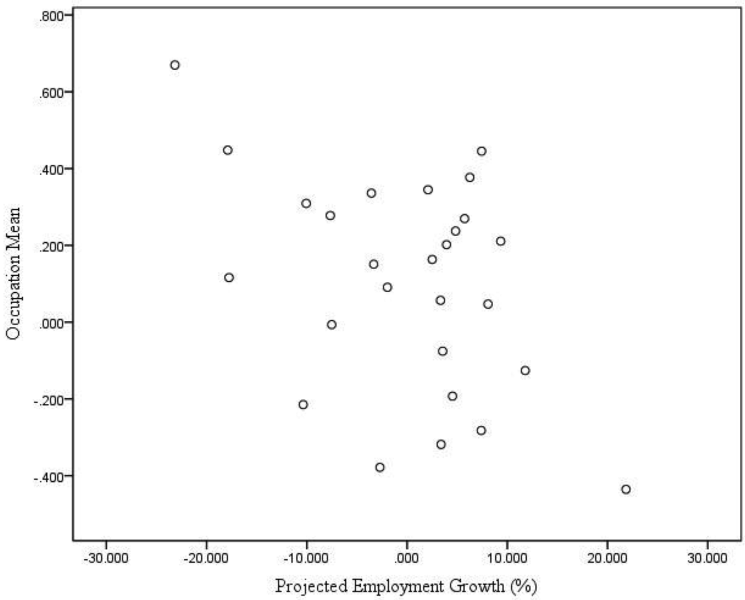
For which grouping option are the estimates best? Due to the low reliability for the occupation-specific slope estimates from the earlier model in Table 4, the optimal ISCO grouping for this submodel remains the minor group (i.e., ISCO 116).

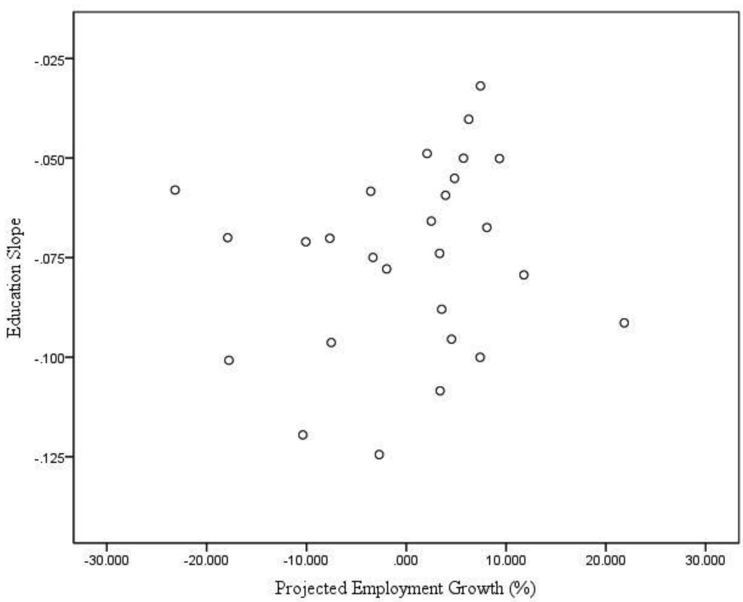
Figure 3 Perceived Group Threat: Empirical Bayes Estimates of the Occupation Means and Education Slopes with Percent Projected Employment Growth (HLM Estimates)

ISCO 9 (N=9)

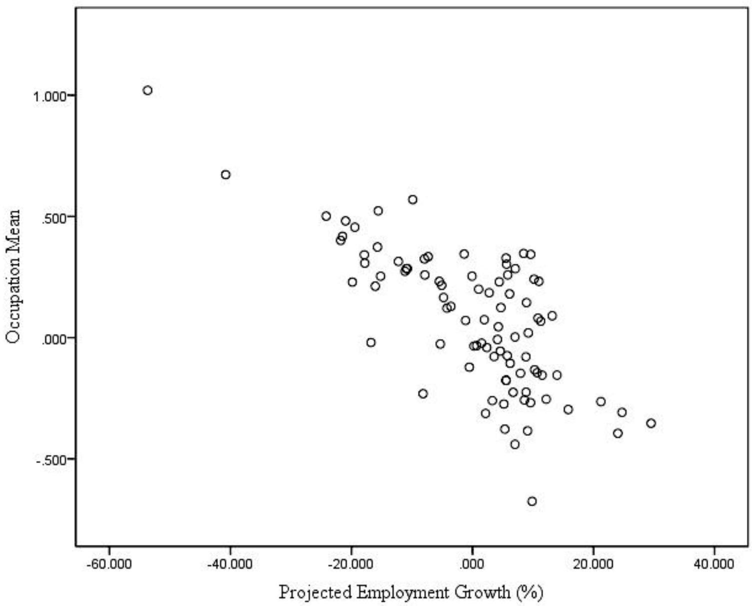


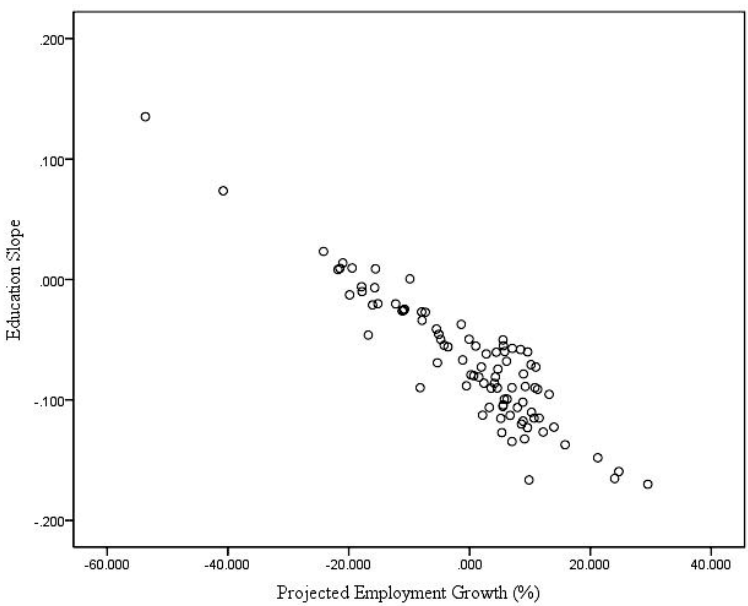
ISCO 28 (N=27)


.800
.600
.400
.200
.000
-.200
-.400
Occupation Mean
-30.000
-20.000
-10.000
.000
10.000
20.000
30.000
Projected Employment Growth (%)

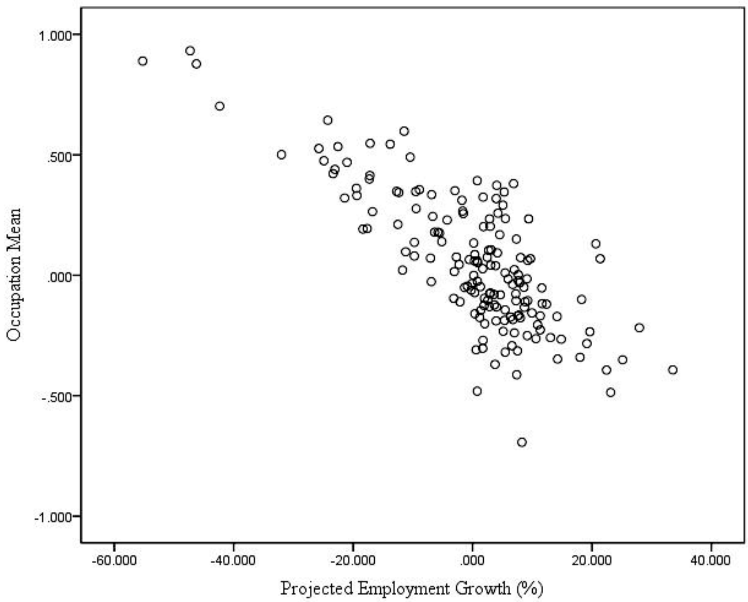

-.025
-.050
-.075
-.100
-.125
Education Slope
-30.000
-20.000
-10.000
.000
10.000
20.000
30.000
Projected Employment Growth (%)

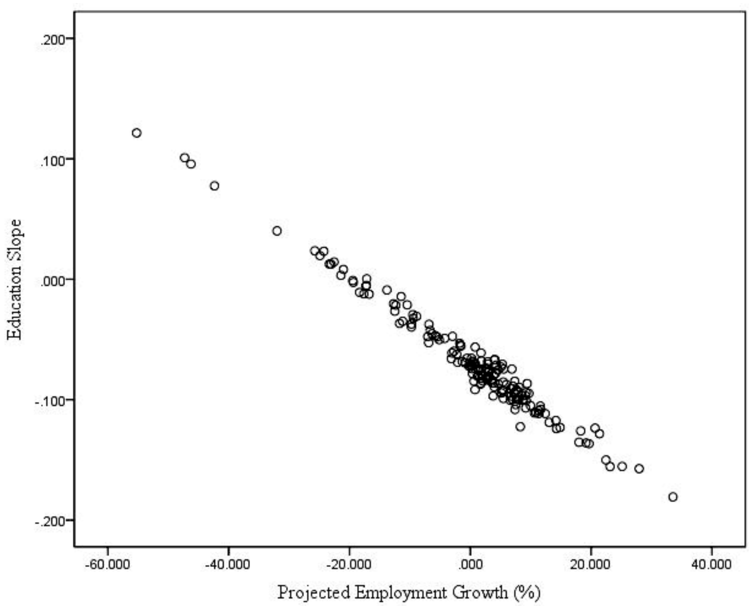
ISCO 116 (N=76)


Occupation Mean
1.000
.500
.000
-.500
-60.000
-40.000
-20.000
.000
20.000
40.000
Projected Employment Growth (%)


Education Slope
.200
.100
.000
-.100
-.200
-60.000
-40.000
-20.000
.000
20.000
40.000
Projected Employment Growth (%)

ISCO 390 (N=116)





CONCLUSIONS

The purpose of this paper is to examine the adequacy of estimates when group-specific sample sizes are small. Research on multilevel modeling suggests that the number of groups is more important than the number of individuals per group. It also suggests rules of thumb for estimating fixed and random effects and variance components with sufficient reliability and power. These indicate that a minimum of 48 groups and reliability coefficients exceeding 0.05 are desirable. Results from three submodels utilizing a different number of groups confirm these guidelines.

Collapsing detailed occupations into a small number of groups, such as the ISCO major (9) and sub-major(28) groups, unnecessarily reduces variation in the intercepts and slopes. When these variances are underestimated, researchers are more likely to conclude that occupations are not relevant units of analysis in studies of anti-immigrant sentiment. Projected employment growth, for example, appears unrelated to perceived group threat and also to the relationship between threat and education when the group-specific sample sizes are increased. Results for the minor (116) and unit (390) groups are more complex. They suggest that maximizing the number of occupations may be a sensible strategy if the purpose of the study is to examine variation in means. A more cautious approach – that is, falling back to a smaller number of occupational groups (116) – seems advisable when the purpose is to examine variation across occupations in slopes.

Although anti-immigrant sentiment is the focus of this paper, these conclusions are applicable to anyone interested in exploring the impact of occupations on people. Although occupations have served as a unit of analysis in some studies – for example, in studies of wage inequality (Cohen and Huffman 2007; Grodsky and Pager 2001; Kaufman 2002) – it is more common for researchers to use one of two strategies. First, occupation-level data have been disaggregated to the individual-level and the nesting of people within occupations has been ignored. Sometimes the researcher has chosen this strategy purposefully. Other times, this has been done without thought, such as when we use occupational prestige scores while analyzing secondary survey data. Disaggregating data and ignoring the nested nature of the data, of course, can lead to serious statistical consequences (Raudenbush and Bryk2002).

Second, some researchers incorporate dummy variables to control for the hierarchical nature of the data (e.g., by including dummy variables for eight of the nine ISCO major groups) or to measure other concepts (e.g., “skill,” see Mayda 2006). Including occupation dummy variables is not an appropriate strategy in most situations because occupational classification systems have too many categories. Including a dummy variable for each category would quickly deplete the degrees of freedom. As we have already seen, condensing data from detailed occupations into a smaller number of categories would throw away a tremendous amount of variability. Dummy variables also do not provide an adequate way to measure occupation-related concepts, such as "skill." Occupations differ in any number of ways; dummy variables may indicate a difference across occupations, but they cannot pinpoint the source of these differences.

This study suggests that researchers interested in occupation effects – regardless of the outcome of interest – can choose an alternative path. It is possible to treat detailed occupations as a unit of analysis in multilevel studies. Doing so allows the researcher to control for the nested nature of the data and also to include more direct measures of occupation-related variables. Instead of using a handful of occupation dummy variables to measure "skill," for example, one could use O*NET data to create scales that directly measure cognitive, physical and social skills and then link these scales to the individual-level data in a multilevel study. Data from the European Social Survey and the International Social Survey Program are well-suited for multilevel studies focusing on occupation effects. Both series contain data for a large number of countries and topics as well as ISCO codes that provide several acceptable levels of detail.

In sum, although sample size considerations are important and all researchers should examine the adequacy of their models, these analyses do not suggest that other approaches (e.g., pooling waves of data, grouping cases, utilizing resampling procedures) may be necessary when facing small occupation-specific sample sizes. It is hoped that these findings will lead to the development of more complex theoretical models of anti-immigrant sentiment where serious thought is given to what the contextual units of analysis should be.

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APPENDICES

Appendix Table A1 Perceived Threat: Exploratory Factor Analysis Results (Principal Component Analysis).

There are different opinions about immigrants from other countries living in America (By "immigrants" we mean people who come to settle in America).How much do you agree or disagree with each of the following statements? [Agree strongly, agree, neither agree nor disagree, disagree, strongly disagree]	Factor Loading
Immigrants take jobs away from people who were born in America[a]	0.773
Immigrants are generally good for America's economy	0.816
Immigrants improve American society by bringing in new ideas and Cultures	0.784
Immigrants increase crime rates[a]	0.742
Percent of variance	60.7
Cronbach's alpha	0.781
N	1,109

a. Reverse coded