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Demonstrating How to Best Examine Group-based Segregation: A Statistical and Conceptual Multilevel Approach

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Abstract

Segregation between ethnic or sociodemographic groups represents a longstanding key independent and dependent variable for the social sciences. However, researchers have only recently begun to take advantage of inferential rather than descriptive statistical techniques in order to assess various aspects of segregation. Specifically, this paper shows that the multilevel binomial response approach suggested by Leckie et al. (2012) provides a particularly flexible framework for describing and explaining segregation in ways not previously possible. Taking the index of dissimilarity (*D*) as an example we demonstrate how the multilevel binomial response approach helps to reduce the problem of small unit bias, allows to asses segregation at different scales and enables researchers to better understand the role of individual- and contextual-level explanatory variables in shaping segregation. To this end, we employ three case studies focusing on different manifestations of ethnic and gender segregation using survey data from urban, national and cross-national settings.

Keywords: index of dissimilarity, segregation, composition, context, multilevel modelling, simulation

An important question in comparative social science research is this: To what extent and why do members of different groups live or work segregated from another? For example, ethnic residential segregation – broadly defined here as the extent to which members from distinct ethnic groups are unequally distributed across residential areas – is often seen as a core independent variable driving multiple forms of ethnic inequality, e.g. in education or on the labour market (Lieberson 1980). Likewise, several social science approaches seek to understand the factors shaping ethnic residential segregation as dependent variable (Massey 1985, Alba and Logan 1993). Segregation, however, is certainly not limited to occur between members of different ethnic groups or with regard to residential areas only. To name just one further example, a longstanding and influential literature deals with the causes and consequences of differences in the distribution of men and women across occupations and related settings, a phenomenon known as gender segregation in the labour market (Chafetz 1988). Empirically, in order to assess different forms of segregation researchers commonly rely on official census data. For sheer size and scope alone, such data certainly represent a very broad and hence useful empirical source. However, the administrative and financial constraints to obtain census data often still are far from trivial. Also, the availability of census data sometimes is restricted to aggregate data only. While sufficient for several purposes, aggregate data might not always meet the requirements of the research question of interest. At this point, the increasing availability of large-scale survey data in conjunction with recent statistical and computational advances opens up new possibilities for research on segregation. Accordingly, this contribution seeks to illustrate the synergies to be achieved when using publicly available survey data in concert with state-of-the-art inferential methods of data analysis in order to adequately describe and explain segregation in different fields. We do so by demonstrating the virtues of using the multilevel binomial response approach to assess segregation recently developed by Leckie et al. (2012). As we explicate below, this statistical framework enables researchers to draw inferential rather than descriptive conclusions, to account for small unit bias, to assess segregation at multiple scales as well as to evaluate the contribution of explanatory variables at different levels of analysis. Given multiple forms of segregation and researchers' interest to quantify segregation by a single number, today a great variety of different so-called segregation indices is available (Massey and Denton 1998). While we endorse this plurality of segregation measures, for pragmatic reasons here we focus on the index of dissimilarity (*D*) as a particularly well-known and popular measure of segregation.

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Modelling the Index of Dissimilarity

The index of dissimilarity (*D*) is perhaps the most widely used measure in the social sciences when interest lies in quantifying the degree to which two groups A and B are unevenly distributed across *J* units. *D* often is defined as (Duncan and Duncan 1955)

$$D = \frac{1}{2}\left(\sum_{j=1}^{J}\left|\frac{a_j}{A} - \frac{b_j}{B}\right|\right) \tag{1}$$

Here, a_j is the observed proportion of group A in unit j, b_j the corresponding observed proportion of group B in unit j and A as well as B refer to the total proportions of groups A and B (Duncan and Duncan 1955). *D* ranges from 0 to 1 where 0 indicates no segregation and 1 describes a scenario with total segregation. Values of *D* within this range are commonly interpreted as the fraction of either group A or B that would have to change across units *J* in order to achieve an even distribution across the *J* units. While intuitively appealing and easy to compute using simple cross-tabulation, researchers long have noticed several limitations of *D*. For example, researchers typically calculate *D* from observed proportions. An important drawback of this approach is that it fails to recognize the underlying stochastic processes that generate these proportions (Leckie et al. 2012). This means that even if the allocation of individuals to units (i.e., ethnic minority and majority members to neighborhoods, men and women to occupations) was purely random, *D* will most likely be non-zero due to random sampling that drives unevenness in the distribution to some non-negligible extent. Further, this upward bias in *D* is known to systematically vary with the proportions of individuals per unit such that the likelihood of observing highly segregated units is inversely related to unit size (i.e., small cell bias, Carrington and Troske 1997, Allen et al. 2009, Mazza and Punzo 2015). Accordingly, when segregation is investigated for a relatively large number of sparsely populated units, random sampling alone might produce some highly segregated units, which in turn generates a disproportionate upward bias in *D*. Drawing on earlier work by Goldstein and Noden (2003), Leckie et al. (2012) developed an elegant statistical solution that overcomes these limitations. These authors demonstrate that a binomial response multilevel model effectively takes into account the binomial sampling variation when modelling observed proportions of individual observations in units and reduces the risk of small cell bias. Statistically, this approach takes advantage of multilevel shrinkage (Raudenbush and Bryk 2012) where units with fewer observations contribute less to the estimation of parameters compared to units with more observations. Consider the following basic two-level binomial response multilevel model:

$$
\begin{aligned}
&y_i \sim Binomial\left(n_j, \pi_j\right) \\
&\text{logit}\left(\pi_j\right) = \beta_0 + u_j \qquad (2) \\
&u_j \sim N\left(0, \sigma_u^2\right)
\end{aligned}
$$

where y_j denotes the probability that an individual in unit *j* belongs to group A, n_j is the total number of individuals in units *j* and π_j is the unknown underlying proportion of group A in unit *j*. The underlying proportion π_j is determined by $\beta_0 + u_j$ through a logit link. β_0 denotes the intercept and when exponentiated represents the average proportion of group A in the 'median' unit *j*. u_j denote the random effects varying across units *j*. The random effects u_j are central to the multilevel framework of segregation because they effectively serve as a naïve estimator of the degree of segregation across unit *j:* the larger the random effects, the larger the variation of the average proportion of group A across units *j*. Conversely, if u_j is zero, then the proportion of group A across unit *j* is constant and therefore no segregation is observed. Once we obtained the estimates for the model described in equation (2), we can calculate *D* using a simulation approach described in Leckie et al. (2012) to compute adjusted counts per unit where M is the number of iterations. Specifically, the simulation proceeds in four steps that build incrementally:

Step 1: Simulate one value for each of the J unit-level random effects using the model estimate of the unit-level variance $\sigma_u^2 : u_j^{(m)} \sim N\left(0, \sigma_u^2\right)$.

Step 2: Compute the estimated proportion of group A per unit $j : \pi_j^{(m)} : anti - \text{logit}\left(\beta_0 + u_j^{(m)}\right)$.

Step 3: Compute the adjusted counts of group A per unit $j : n_j^{(m)A} = \pi_j^{(\mathrm{m})} n_j$; with the adjusted counts of group B per unit j computed as $n_j - n_j^{(m)A}$.

Step 4: The dissimilarity index is then computed as

$$
D^{(m)} = \frac{1}{2}\left(\sum_{j=1}^{J}\left|\frac{n_j^{(m)A}}{\sum_{j=1}^{J} n_j^{(m)A}} - \frac{n_j^{(m)B}}{\sum_{j=1}^{J} n_j^{(m)B}}\right|\right) \qquad (3).
$$

Summarizing the resulting vector of M dissimilarity indices by its mean and the corresponding 95% confidence interval yields the desired measure of uncertainty. In this way, uneveness due to binomial sampling variation respectively small cell bias is adequately taken into account when calculating *D*, with the confidence interval providing additional information about the statistical significance of *D*. However, approaching segregation from a statistical and conceptual multilevel perspective offers additional and equally important advantages. Perhaps most interestingly, the multilevel approach outlined above enables researchers to model segregation as a function of explanatory variables at different levels of analysis. Typical (two-level) applications of multilevel modelling often seek to model between-context variance (e.g., cross-national differences in respondents' average income or explaining school differences in pupils' average math-skills). This level-two variance can potentially be explained by compositional differences across the level-two units, level-two characteristics or a combination thereof (Raudenbush and Byrk 2002, Hox 2010, Snijders and Bosker 2011). Consequently, adding level-one respectively level-two explanatory variables will likely reduce the level-two variance[1]. One issue with this modelling approach lies with the fact that the comparison of nested non-linear models is problematic because the individual level variance is fixed to $\pi^2/3$ (Hox 2010). When including independent variables, parameter estimates of the model will be rescaled in such a way that the variance on the individual level remains constant at $\pi^2/3$. Obviously, this is problematic when these parameter estimates are fundamental to the simulation steps of the multilevel framework. Hence, as one extension of Leckie et al.'s (2012) modelling approach, we aim to remedy this drawback by bringing all models to the same baseline scale of the respective null models through multiplication of all parameter estimates with the squared "scale correction factor" (Hox 2010: 133ff). The scale correction factor is defined as

$$SCF = \sqrt{\frac{\frac{\pi^2}{3} + \sigma^2_{u(0)}}{\frac{\pi^2}{3} + \sigma^2_u + var(\hat{\pi})}} \quad (4),$$

where $var(\hat{\pi})$ denotes the variance of the linear estimator and the index (0) refers to parameters from the null model (i.e., a model to estimate the unadjusted segregation). This correction is applied throughout all analyses presented in this article.

In terms of multilevel modelling of segregation, a decrease in the random effects means that some part of the observed segregation pattern is due the explanatory variables added to the model[2]. Apparently, this option is particularly advanta-

1 In some instances, adding level-1 variables may increase level-2 variation. Typically, this occurs when variables are added to the model that contain no or only very little between-unit variation (Hox 2010: 74). For instance, the sex distribution across city districts is unlikely to vary substantially thus adding individual's sex may increase the variation on the district level. Dropping variables with little level-2 variation should solve the issue.

2 Kalter (2001) proposed a multinomial logit framework to adjust D for compositional differences across two groups. However, this framework does not take into account small cell bias nor does it enable researchers to add unit-specific explanatory variables of the observed segregation patter ns (e.g., occupational characteristics or neighborhood characteristics).

geous for examining the individual respectively contextual level factors presumed to generate or maintain segregation between groups. At the same time, conceptualizing segregation in a multilevel framework opens up the possibility to model segregation across multiple scales. Thus, in terms of residential segregation, this means that one could model segregation with respect to neighborhoods and cities in one model by introducing a hierarchical city level (level 3) in addition to the neighborhood level (level 2) and individual residents (level 1). Note that this framework also can easily incorporate non-hierarchical segregation structures using a cross-classified design, e.g. occupational and industrial gender segregation (see study 3).

Three Case Studies

In the empirical part of our paper, we present three case studies of modelling *D*. These examples illustrate not only different modelling options offered by the proposed new method, but also provide novel answers to interesting substantial research questions. The first example presented in study 1 uses data from German urban monitoring survey in which German citizens and immigrants were sampled from a large number of city districts. These data enable us to study the extent of ethnic residential segregation between city districts, holding constant socioeconomic differences among respondents and accounting for district-level characteristics. The second example presented in study 2 directs its attention to the field of cross-national research. Using individual data from the European Labour Force Surveys (EU-LFS), we study the degree of ethnic occupational segregation for 15 EU member states that remains after both individual- as well as occupation-level explanatory variables are taken into account. In study 3, the research question of interest for the final example is to determine simultaneously the level of gender occupational and industrial segregation. To this end, we employ a cross-classified multilevel model using a single wave from the German Socio-Economic-Panel Study (GSOEP).

Study 1: Ethnic Residential Segregation

Data and Theory

We study ethic residential segregation using data from the urban monitoring survey program of the city of Duisburg (‘Duisburger Bürgerumfrage’, see GESIS 2017), a large multiethnic city situated in the western part of Germany (see Schlueter, 2011). Focusing on topics such as residents’ satisfaction with the cultural and social infrastructure of the city, these surveys were carried out separately for German citizens and foreigners using random samples of individuals aged 18 years and older selected from the city's population register. For the present purposes and in order to increase sample size, we merged three waves of data spanning the years 2004, 2005 and 2006 (Stadt Duisburg, Amt für Statistik, Stadtforschung und Europaangelegenheiten der Stadt Duisburg, 2007). From the sample of foreigners, we selected only Turkish respondents[3] as they represented the largest ethnic minority group in Duisburg (~24 percent). Our final sample covers 6,352 individuals (level 1), 21 percent of which from Turkish descent, living in one of 46 districts in the city of Duisburg (level 2). The dependent variable in this case study is a dichotomous variable indicating whether respondents are of Turkish descent (1) or of German descent (0).

We employ three theoretical perspectives to describe and explain ethnic residential segregation. Our vantage point is the spatial assimilation model (Massey, 1985), which posits that ethnic minority members are able to convert their socioeconomic resources for renting or acquiring living space that is equally desired by ethnic majority members. According to this approach, the extent of ethic residential segregation should diminish once the socioeconomic resources of group members are taken into account. To this end, we include three individual-level indicators reflecting group compositional differences in socioeconomic resources (highest education attainment [1 = no education to 3 = (Fach-) Hochschulreife], respondent receives unemployment benefits and respondent receives social welfare). For completeness, we also hold constant respondents' age (in years), gender (0 = male, 1 = female), marital status (0 = not married, 1 = married) and household size (number of persons per household). Unlike the spatial assimilation model, the place stratification model holds that ethnic residential segregation centrally is shaped by powerful majority members (e.g. real estate agents, landlords) who seek to constrain ethnic minority members' access to desirable residential spaces (Alba and Logan, 1993). Supposing that a substantial degree of ethnic residential segregation persists even after controlling for differences in the socioeconomic resources of group members, this means that more (less) attractive districts should increase (decrease) ethnic residential segregation. We seek to approximate these assumptions by assessing the desirability of city districts using information on the average living space per person (2005 data) and average rent per square meter (no utilities, 2002 data), presuming that a higher average living space per person respectively higher average rent per square meter indicates more attractive city districts. Further, we take the number of social welfare recipients per 1,000 inhabitants (2005 data, Stadt Duisburg 2007) to indicate less attractive city districts. The third theoretical account we consider is known as the homophily-principle. Shifting attention to group members' ethnic preferences, this approach presumes at its core that ingroup members prefer to dwell among fellow ingroup members (Schelling 1969; McPherson, Smith-Lovin and Cook 2001; Henry, Pralat and Zhang 2011). We approximate

3 Extending this example to multigroup comparison is fairly straightforward using multinomial logistic multilevel models or a series of binomial multilevel models.

this assumption using data on the local ethnic infrastructure represented by the proportion of 'ethnic clubs' per postal code district gathered from the Federal Register for Associations (Justizministerium 2016).

Results

Figure 1 depicts the results for the gross level of ethnic residential segregation and the subsequent adjustments for compositional differences between Germans and Turks as well as contextual differences across city districts. The first two bars of the figure show that the gross level of ethnic residential segregation is fairly similar when calculated based on the standard cross-tabulation approach and the multilevel simulation approach. Both methods result in an index of dissimilarity that approaches a value of 0.40. In addition, the simulation results provide a 95% confidence interval depicted as error bars which range from 0.31 to 0.47. According to the common interpretation of *D*, in order to for the two population groups to be evenly distributed across Duisburg's city districts, roughly 40 percent of the population would need to move between districts. However, adjusting the observed level of residential segregation for potential compositional differences between Germans and Turks in terms of their socioeconomic resources results in a decline to an average of 0.28 (CI=[0.22;0.35]). In other words, around one quarter of the observed level of ethnic residential segregation in Duisburg is accounted for by the average lower socioeconomic positions of Turks relative to Germans – a large effect.

Table 1 presents the results of the multilevel models which provided the parameters for the simulation of the dissimilarity index, specifically, the intercept and the district-level random effect. Assessing the direction of change in segregation after adjustment for compositional differences is easily glimpsed by the reduction of the district-level random effect which decreases from 1.08 to 0.58 (Variance district-level$\times$SCF^2=0.97$\times$0.60~0.58). Hence, even without carrying out the simulation of *D* the change in the district level variance provides an intuitive measure of the change of segregation: the variance on the district level indicates how strongly the average proportion of Turkish residents per city district deviates from the median neighborhood. Thus, a reduction in this variation implies that some fraction of the between-district variation in the proportion of Turkish residents is accounted for differences in the socioeconomic composition of the two groups.

Finally, model 2 incorporates the contextual measures of the local pricing structure and ethnic infrastructure which results in a further decrease in the level of segregation to an average of 0.17 (CI=[0.13;0.21]). Contrary to our expectation, we do not find that the proportion of ethnic clubs is associated with the proportion of Turkish inhabitants per neighborhood. The pricing indicators are more in line with our expectations: city districts with on average larger rooms have lower proportions of Turkish inhabitants whereas the number of social welfare recipients per 1,000 inhabitants is positively associated with a districts' proportion of Turks. Although

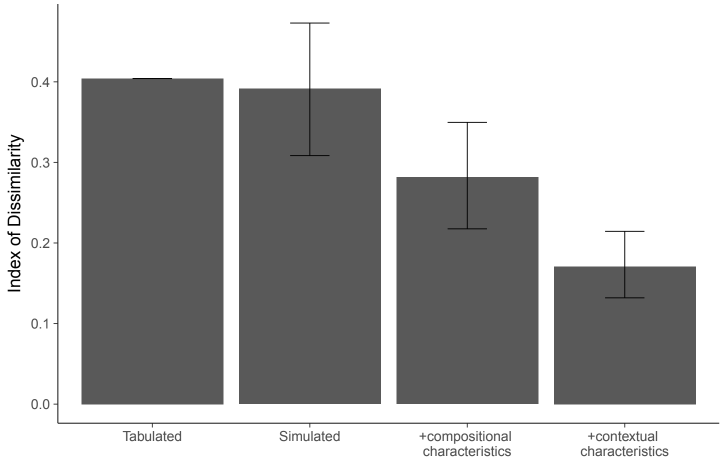

Figure 1 Ethnic residential segregation in Duisburg, calculated based on tabulated data and using multilevel binomial response approach

these associations are present net of individual differences in resource endowment, the associations point towards a primary underlying mechanism, namely that the lower socioeconomic composition of Turks in Duisburg constraints their residential choices which in turn is associated with a large part of the observed segregation patterns. Overall, the adjustment of segregation for compositional and contextual differences reduced the index of dissimilarity by roughly 60 percent[4].

Study 2: Ethnic Occupational Segregation

Data and Theory

In order to study ethnic occupational segregation, we rely on cross-national data from the European Labour Force Survey (LFS) for the EU-15 member states. For this application, we focus on comparing occupational choices of first generation immigrants (i.e., those born outside the respective destination country) to the national population. Specifically, we use data from the 2009 wave covering (self-) employed individuals aged 22 to 57. Occupations are classified according to three-digit ISCO-88 codes which provide a suitable compromise between level of detail (i.e., 131 distinct occupational categories) and individuals per occupational category. Moreover, the analyses will be carried out separately not only by country,

4 Notice that and variance on the neighborhood level is reduced by roughly 80 percent. This difference is due to the non-linear relation between the random effects and the dissimilarity index (Leckie et al. 2012:15).

Table 1 Multilevel modelling of ethnic residential segregation in Duisburg, 2003-2006 (n=6,532)

	M0: gross D		M1: + individual characteristics		M2: + contextual characteristics	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Intercept	-1.59*	0.16	-2.86*	0.18	-2.78*	0.14
Age			-0.03*	0.00	-0.04*	0.00
Female			-0.43*	0.08	-0.44*	0.08
Married			1.57*	0.11	1.56*	0.11
Household size			0.50*	0.03	0.50*	0.03
Group compositional differences						
Education						
No education			2.40*	0.14	2.38*	0.14
Hauptschule			0.70*	0.12	0.68*	0.12
Realschule (ref.)						
(Fach-)Hochschulreife			0.03	0.15	0.04	0.15
Receives unemployment benefits			0.99*	0.13	0.97*	0.13
Receives social welfare			0.72*	0.19	0.71*	0.19
Contextual differences						
Average room size					-0.08*	0.03
Average price per qm					-0.41	0.23
Social welfare recipients per 1,000 inhabitants					0.01*	0.00
Proportion of ethnic clubs					-0.94	1.29
Variance neighborhood level	1.08		0.97		0.38	
SCF^2	-		0.60		0.53	
R^2 neighborhood level	-		0.55		0.84	

Note. All variables (with the exception of "education") grand-mean centered. Comparisons across models require multiplication of M1 and M2 coefficients with the squared scale correction factors.

but also by gender – an important category in research on labour market segregation. Our final sample includes 1,082,025 individuals (11.2 percent of which are immigrants) living in one of the EU-15 member states. The dependent variable in this case study is a dichotomous variable indicating whether respondents were born outside their country of residence (1) or born in the country of residence (0).

Labour market outcomes such as occupational sorting typically result from matching processes between employers wanting to fill vacancies with suitable candidates and employees expecting to receive adequate compensation for the skills they offer (Kalleberg and Sørensen, 1979). Systematic differences in occupational sorting between immigrants and the majority population may therefore result from (1) between-group differences in the skills they offer or (2) preferences of employers for individual characteristics that go beyond skill endowment (i.e., discrimination; Granato and Kalter 2001). Since discriminatory explanations are notoriously difficult to uncover with large-scale survey data, we focus on the first aspect, namely compositional differences between immigrants and the majority population in terms of relevant skills. Central to group differences regarding skills will be educational attainment as a first crude approximation where higher levels of education are assumed to be associated with higher skill levels. This approximation obviously ignores substantial variation in labour market skills within educational categories. We try to improve the approximation by including occupational characteristics that are correlated with differences in skill level. For example, two occupations may be chosen by individuals with similar educational attainment profiles. But these occupations differ along other dimensions (e.g., the prevalence of temporary employment contracts) that make them more or less attractive to the higher skilled employees and thereby help in explaining group differences in occupational sorting beyond mere compositional differences in the absence of adequate data. Hence, when trying to account for the observed degree of ethnic occupational segregation, we include the following individual characteristics (i.e., compositional differences between immigrants and the majority population, level 1) as well as contextual characteristics (i.e., differences between occupational categories, level 2). For the first set of characteristics, measures of age (in years), marital status (0=not married, 1=married), nationality (0=nationalized, 1=non-national), educational attainment (0=ISCED to 6=ISCED 6), weekly work hours and full-time employment (0=part-time, 1=full-time). In contrast to the data used in case study 3, the EULFS includes few relevant occupational characteristics. We therefore rely on aggregating country-specific individual characteristics for each occupational category: the percentage of firms employing more than 10 workers, the percentage of workers holding temporary contracts and the percentage employed in non-shiftwork. Results for the simulated index of dissimilarity *D* are based on gender- and country-specific multilevel binomial response models where employees (level 1) are hierarchically nested in 131 occupational categories (level 2).

Results

Figure 2 visualizes the results for modelling ethnic occupational segregation separately for men (upper panel) and women (lower panel) across 15 European-Union countries. To begin with, we note that the figure shows substantial cross-national variation in the extent of *D*. For males, the results for simulating *D* from the initial models without individual- respectively occupational-level explanatory characteristics range from a minimum of 0.18 (Belgium) to a maximum of 0.49 (Greece). For females, the minimum in ethnic occupational segregation equals 0.15 (Belgium), while its maximum is 0.52 (Greece). To illustrate, these numbers could be taken to imply that in Belgium, 18% of the first generation male immigrants and majority members would need to change between occupational categories in order to achieve an equal distribution across all occupations. However, the results from the subsequent models demonstrate that the extent of ethnic occupational segregation is substantially reduced once the previously discussed explanatory variables are taken into account. For all countries and for both males and females, controlling for compositional characteristics of the individual employees uniformly results in a decrease of D. For example, the largest drops in D are found for Italy (for male employees, $\Delta D = 0.24$; for female employees, $\Delta D = 0.19$). To reiterate the logic of the underlying modelling approach, we note that parts of the level-2 variance, which in this case reflects how strongly the proportion of immigrants varies across occupations, are accounted for by differences in, for instance, educational profiles or weekly work hours between immigrants and the respective host society populations. Conversely, the remaining level-2 variance suggest that even after accounting for these compositional differences, immigrants are still disproportionately more often working in some occupations rather than others. This implies that there are either compositional differences we haven't picked up yet and/or that these differences can be explained by systematic difference of occupations themselves. The figure also shows that adding the occupation-level characteristics to the model leads for many countries to a further, albeit relatively small decrease in the extent of ethnic occupational segregation. Interestingly, between countries the data reveal a heterogeneous pattern of results between occupational characteristics and the proportion of (male) immigrants in each country-specific occupational category. For example, whereas an occupations higher prevalence of shift work is positively associated with a higher share of immigrants in Germany, Greece, Italy, Spain and the UK, no such correlation is present in the remaining EU-15 countries. Similarly, in some countries immigrants seem to overrepresented in occupations typically present in smaller firms in some countries: in Belgium, Greece, Italy and Spain, the results show that the higher an occupation's proportion of individuals working in firms with more than 10 employees, the smaller that occupation's proportion of immigrants. However, in the remaining countries this association is virtually absent[5]. Collectively, these results could be taken to explore potential country-level moderators of the divergent relations between the predictors and the proportion of (male) immigrants in the occupational categories.

5 Table A1 in the appendix summarizes the pattern of results. Detailed results are available upon request.

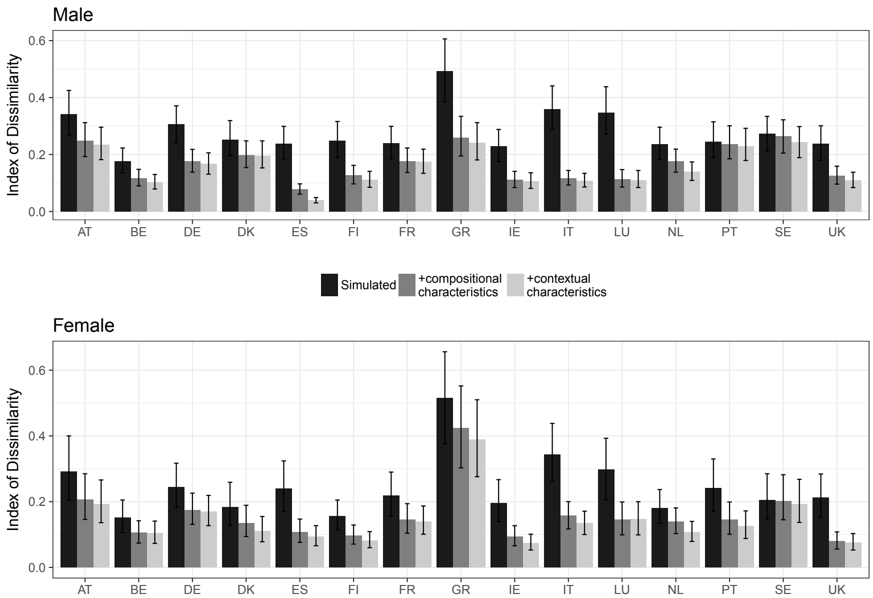

Figure 2 Ethnic occupational segregation in EU-15 countries based on multi-level simulation approach

Study 3: Occupational and Industrial Gender Segregation

Data and Theory

For the third case study, we rely on data from the German Socio-Economic Panel Study (GSOEP, Wagner et al. 2007), which has been collected annually since 1984 as a probability-based sample of households. We use the 2011 wave and restrict the sample to (self-) employed individuals aged 25 to 54. Information on occupations is again based on three-digit ISCO-88 codes. Because we are also interested in estimating the level of gender industry segregation that is independent of occupational segregation, we rely on the division categories of the NACE classification of industries which comprises a total of 62 categories (e.g., 'crop and animal production', 'manufacturing of electrical equipment' or 'education'). In total, the sample covers 7,802 employees working in 108 occupations and 62 industries. The dependent variable in this case study is a dichotomous variable indicating whether respondents were female (1) or male (0).

Similar to the mechanisms that generate patterns of ethnic occupational segregation, occupational segregation is a result of women and men systematically sorting into different occupations. The reasons for this differential sorting are broadly associated with gender-specific preferences in occupational characteristics as well as differences in (anticipated) life course pressures (Ostner 1990; Hakim 2002; Padavic and Reskin 2002). According to socialization theory, occupational preferences are established in earliest socialization with individuals adopting gendered skills to varying degrees. Gendered preferences may lead individuals to opt for jobs where these skills are more advantageous such as occupations with a strong "social" or "caring" component in the case of women; occupations which are typically part of the service sector (Busch 2013). In addition, different stages in the life course are associated with specific pressure on individuals to reconcile family and employment (Filer 1989; Tam 1997). These pressures are especially marked for women with (small) children who therefore more often work part-time or in jobs with higher flexibility (Glass and Camarigg 1992; Bush 2013; Cha 2013).

Hence, in order to account for the extent of occupational and industry segregation in Germany, we include measures that aim to capture differences in life-course stages and occupational characteristics indicative of job higher flexibility. In terms of life-course stage, we include individual-level measures for marital status (1=married, 0=else), household type (1= single household, 2= single parent household, 3= two person household, no children present, 4= two parent household, at least one children younger than 16 years present, 5= two parent household, children 16 or older present, 6=other), the number of children present in the household who are younger than 16, the total years of full-time work experience and the number of years individuals worked with their current employer. Flexibility differences are captured using the following individual-level characteristics: respondent works part-time, respondent holds a managerial position and works in service industry. In addition, we include occupation-level characteristics which were computed from the SOEP data: the percentage of public employees, percentage working in the service industry, percentage of individuals working in the occupation they trained for, average status of occupation (based on ISEI scores), average company size and average job autonomy. And finally, we also include respondent's education based on the six category ISCED 1997 classification. Notice that occupations and industries are not necessarily nested within another; for example, a white or blue collar workers can certainly work in different industries, and vice versa. Thus, a more realistic view is to consider employees to be situated in a cross-classification of jobs and industries, and this is why we use a non-hierarchically cross-classified multilevel model (Raudenbush and Bryk 2012). Accordingly, in this example, we take employees (level 1) to be non-hierarchically nested in both occupations (level 2a) and industries (level 2b). Our results are based on cross-classified multilevel binomial response models where employees are non-hierarchically nested in 108 occupations and 62 industries.

Results

The main results for this case study are presented in Figure 3. The index of dissimilarity based on cross-tabulated data is calculated as 0.52 for occupational gender segregation and 0.39 for industrial gender segregation. The corresponding values from the multilevel simulation approach are 0.45 (CI=[0.38;0.52]) for occupational and 0.18 (CI=[0.13;0.25]) for industrial gender segregation. Hence, there is considerably less agreement in the extent of segregation compared to the findings presented for residential segregation above. That is because the calculation based on cross-tabulated data is only two-dimensional and thus cannot take into account deviations from unevenness due to some other but possibly related grouping factor. The same is not true for multilevel simulation approach: here, additional grouping factors are taken into account by simply modelling them. The corresponding random effect is estimated net of other random effects present in the models. The differences between the tabulated and simulated indices of dissimilarity thus indicate that some part of occupational segregation is due to industrial segregation and vice versa. Though, apparently it is primarily industrial gender segregation that is artificially inflated due to not taking into account occupation-level random effects.
The following bars in Figure 3 depict the simulated dissimilarity index when adding employee characteristics to the models (see Table 2, model M1 for detailed results). As expected, differences in employee characteristics explain parts the variance in

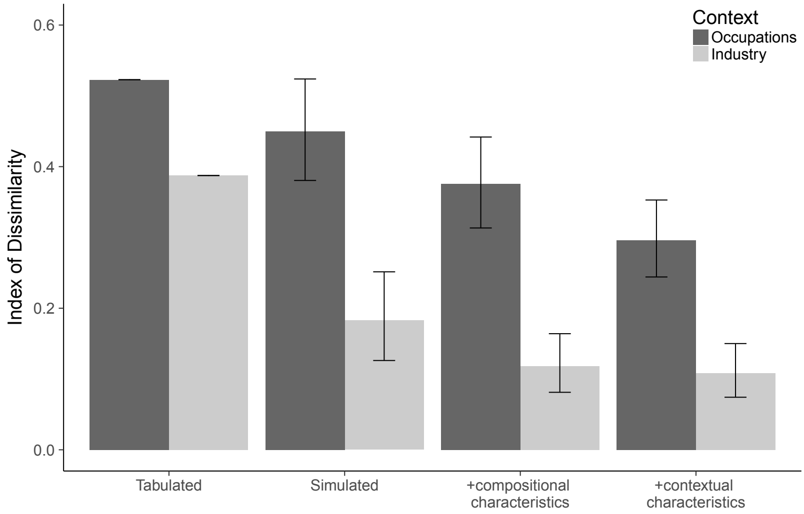

Figure 3 Occupational and industrial gender segregation in Germany, calculated based on tabulated data and using cross-classified multilevel binomial response models

the proportion of women across occupations and industries: levels of segregation decrease to 0.38 (CI=[0.31;0.44]) for occupations and to 0.12 (CI=[0.08;0.16]) for industries. Thus, on average 16 percent ([0.45-0.38]/0.45) of occupational gender segregation are due to employees with specific characteristics differentially sorting across occupations: for example, some occupations are more frequently composed of individuals working part-time or in service industries. And because these characteristics are more prevalent among women, the inclusion of their attributes in the simulation models accounts for some of the observed unevenness in the gender distribution across occupations. Similarly, differences in employee composition account for roughly 33 percent of industrial gender segregation. And finally, adding characteristics of occupations to the model further decreases the simulated segregation to an average of 0.30 (CI=[0.24; 0.35]) for occupations and to 0.11 (CI=[0.07; 0.15]) for industries. According to the estimates presented in M2, occupations with a higher percentage of employees working in service industries also tend to have a higher proportion of women working in them. None of the other occupational characteristics covary with the proportion of women per occupation. Occupational characteristics account for an additional 15 percentage points in occupational gender segregation and another 5 percentage points in industrial gender segregation through differences across industries regarding their occupational make-up. Even though we included a broad range of factors associated with differences in life-course stages and flexibility demands, especially the extent of occupational gender segregation remaining is substantial: around one third of female or male employees would need to change occupations to arrive at an even distribution.

Table 2 Multilevel modelling of occupational and industry gender segregation, GSOEP 2011 (n=7,802)

	M0: gross D		M1: + individual characteristics		M2: + contextual characteristics	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Intercept	-0.50*	0.17	-0.10	0.29	0.01	0.28
Educational attainment			-0.01	0.03	-0.01	0.03
Group compositional differences						
Married			0.48*	0.08	0.48*	0.08
Household type (ref. other)						
Single household			-0.10	0.26	-0.09	0.26
Single parent household			1.28*	0.29	1.30*	0.29
Two person household			0.14	0.26	0.15	0.26
Two parent household, at least one child younger than 16 present			-0.71*	0.27	-0.70*	0.30
Two parent household, children 16 or older present			-0.24	0.26	-0.23	0.26
Number of children younger than 16			-0.17*	0.07	-0.17*	0.07
Total years of full-time work experience			-0.07*	0.01	-0.07*	0.01
Number of years worked with current employer			0.02*	0.01	0.02*	0.01
Works part-time			2.20*	0.11	2.19*	0.11
Holds managerial position			-0.50*	0.09	-0.51*	0.09
Works in service industry			0.46*	0.14	0.35*	0.14
Contextual differences						
Percentage of public employees					-0.75	0.63
Percentage working in service industry					2.52*	0.48
Percentage working in occupation they trained for					-0.27	0.64
Average occupational ISEI					0.01	0.01
Average job autonomy					-0.12	0.30
Variance occupation level	2.03		1.67		1.07	
Variance industry level	0.24		0.13		0.13	
SCF^2	-		0.74		0.63	
R^2 occupation level	-		0.39		0.67	
R^2 industry level	-		0.60		0.66	

Note. All variables grand-mean centered. Comparisons across models require multiplication of M1 and M2 coefficients with the squared scale correction factors.

Discussion

In this article we sought to demonstrate how using a standard multilevel binomial response model in an atypical way enables researchers to overcome several limitations that long have hindered research on segregation. In following Leckie et al. (2012), we showed how the upper-level variances from a binomial multilevel model can be effectively used as accurate measure of ethnic and gender segregation. Further, by employing simulation techniques we then converted this measure into the popular and well-known index of dissimilarity D. This methodological strategy helped not only to avoid the common inflation of D due to small unit bias. In addition, the novel approach also enabled us to assess segregation simultaneously at different scales and to examine the contribution of explanatory variables at multiple, statistically appropriate levels of analysis[6]. Although our primary focus in this paper was methodological, our illustrative case studies yielded several substantial findings that deserve enhanced attention in subsequent research. Specifically, to the literature on ethnic residential segregation this study adds the insight that controlling for individual-level differences in group members' socioeconomic resources drastically reduces the degree of residential segregation (Teltemann, Dabrowski and Windzio, 2015). Unlike previous research, our results show that even after an array of individual-level differences is taken into account, contextual-level characteristics still make a significant contribution to ethnic residential segregation. Relatedly, this study also extends previous knowledge on ethnic occupational segregation. Our findings not only show a substantial decrease in ethnic occupational segregation across several countries once various individual-level factor are taken into account. In addition, the results also offer new insights of the role occupation-level characteristics play in shaping differences between ethnic majority- and minority at the labour market. With regard to the literature on gender segregation at the labour market, this article is the first that assesses segregation simultaneously at different levels using a cross-classified multilevel model. Doing so yielded the novel finding that what appears at first sight as different distribution of men and women across occupations should be better understood as simultaneous segregation not only at the level of occupations, but also at the level of industries. Apart from these substantial contributions, future methodological developments might expand our knowledge in several directions. For example, in focusing on D, we have explored the issue of using a multilevel inferential framework for a single index of segregation only. However, it is well-known that research on seg-

6 We refer readers interested in applying the methods described here for their own needs to Spörlein, C. (2016). multi.correct: An R package to calculate and correct the Index of Dissimilarity using multilevel/random effects models, available at https://github.com/chspoerlein/multi.correct.git . Simply type multi_correct after loading the package to inspect the code or ?multi_correct for the help file and code examples.

regation offers a particularly rich array of different segregation measures (Massey and Denton, 1985). Indeed, the statistical approach applied in this paper appears to be suitable to several alternative measures of segregation, such as the prominent isolation- respectively interaction-index (see Leckie et al., 2012) or the index of net difference (ND, see Lieberson 1969). It also appears promising to apply the present approach for assessing segregation phenomenon between multiple ethnic or demographic groups. For ease of exposition, in this contribution we restricted our focus on modelling segregation for two groups only. Yet by extending the binomial to a multinomial response model the present approach is also capable to provide accurate estimates of segregation between multiple groups (Jones et al. 2015, Reardon and Firebaugh 2002). Collectively, the insights resulting from such methodological developments will help to better inform our theoretical understanding of the extent and the sources underlying social segregation.

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Appendix

Table A1: Ethnic occupational segregation in EU-15 countries based on multi-level simulation approach. The table shows significantly (p < .05) positive or negative associations of the predictors with the proportion of immigrants per occupational categories

	Age	Non-national	Education	Married	Employed fulltime	Work hours	Average company size	Proportion holding temporary contracts	Proportion without shift work
AT	-	+	-	+		-		+	
BE	-	+	-	+	-		-	+	
DE	-	+	-	+		-			-
DK	-	+	+	+					
ES		+	+	+			-	+	-
FI	-	+		+					
FR	+	+		+					
GR	-	+	+	+			-	-	-
IE	+	+	+	+	-	-			
IT	-	+	+	+			-		-
LU	+	+		+					
NL		+	-	+				+	
PT	-	+	+	+	-				
SE	-	+	+	+				+	
UK	-	+	+	+	-	-			-