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Measuring Segregation When Units are Small: A Parametric Approach

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This article considers the issue of measuring segregation in a population of units that contain few individuals (e.g., establishments, classrooms). When units are small, the usual segregation indices, which are based on sample proportions, are biased. We propose a parametric solution: the probability that an individual within a given unit belongs to the minority is assumed to be distributed as a mixture of Beta distributions. The model can be estimated and indices deduced. Simulations show that this new method performs well compared to existing ones, even in the case of misspecification. An application to residential segregation in France according to parents' nationalities is then undertaken. This article has online supplementary materials.

KEY WORDS: Beta-binomial model; Dissimilarity index; Ethnic concentration; Mixture of Beta distributions.

1. INTRODUCTION

Standard segregation indices measure the distance between the distribution of a minority population across units and a counterfactual situation of *evenness* in which the proportion of minority individuals would be exactly the same in each unit. When units are small, past research has stressed that *randomness*, a counterfactual situation in which the minority individuals are distributed randomly across units, would be a more sensible benchmark than evenness (Cortese, Falk, and Cohen 1976; Boisso et al. 1994; Ransom 2000). The discrepancy arises because segregation indices use the observed proportion π_a of the minority group in unit a to estimate the true unobserved probability p_a that an individual of this unit belongs to the minority. When units are small, π_a is a noisy estimate of p_a and indices are biased. This issue is of practical relevance: analyses that investigate the distribution of employees across firms (Carrington and Troske 1995; Kramarz, Lollivier, and Pelé 1996; Kremer and Maskin 1996; Carrington and Troske 1998b; Bayard et al. 1999; Hellerstein and Neumark 2008), pupils across schools or classrooms (Allen, Burgess, and Windmeijer 2009; Söderström and Uusitalo 2010), or inhabitants across districts or buildings (Maurin 2004) may be directly affected by this small-unit bias.

Following Winship (1977), Carrington and Troske (1997)—hereafter CT—introduced an adjusted index. Their approach is the most frequently used in the applied literature (Carrington and Troske 1998a; Hellerstein and Neumark 2003, 2008; Persson and Sjögren Lindquist 2010; Söderström and Uusitalo 2010) and has been extended to account for the presence of covariates (Aslund and Skans 2009). Allen, Burgess, and Windmeijer (2009)—hereafter ABW—proposed to correct indices by a bootstrap procedure and provide simulations to show its performance. Both CT and ABW emphasized the issue of inference and proposed statistical tests of segregation.

In this article, an alternative method based on parametric assumptions is proposed to deal with the small-unit issue. First, a statistical framework is introduced: the probability p_a is assumed to be a random variable with distribution F . The

distribution of the number of minority individuals in unit a is then a binomial with parameters p_a and the unit size. To compute a distance to randomness, one would like to use p_a instead of the empirical proportions π_a to compute the segregation index. The index based on the unobserved probabilities p_a is the quantity of interest of this analysis. The main contribution of this article is to propose a simple parametric approach to estimate this index of interest: F is assumed to be a mixture of Beta distributions. Under this assumption, the parameters of the distribution and therefore the quantity of interest can be estimated. The model is an extension of the Beta-binomial model and offers an appreciable trade-off between flexibility and parsimony. Both bootstrap and the delta method may be used to provide for inference.

I compare to what extent the existing methods estimate the quantity of interest of this article. In expectation, the CT-adjusted index is shown to be below the quantity of interest when applied to the dissimilarity index, except when the underlying distribution is discrete with three masspoints—on 0, 1, and the mean of the distribution. Simulations are also run to compare the methods proposed by CT and ABW to the one that I propose here, for the dissimilarity, the Gini, and the Theil indices. These simulations show that the correction method relying on the estimation of a Beta mixture performs well in various cases, including those in which the parametric model is misspecified.

Finally, the Beta-mixture correction method is applied to measure the residential segregation of first- and second-generation migrants, according to their country of origin, in France. This case illustrates well the small-unit issue, as the only available data is a survey in which the number of individuals by unit is equal to 30 on average, while the minority groups represent between 0.2% and 6% of the total population.

The next section details the statistical framework and presents the existing methods that attempt to deal with the issue. Section 3

presents the new method introduced in this article. Section 4 shows how the proposed approach performs on simulated data, compared to existing methods. Section 5 presents an application to ethnic residential segregation in the French case.

2. THE PROBLEM AND ITS EXISTING SOLUTIONS

Concentration indices are useful tools to capture the unevenness of the distribution of different groups in different units (Duncan and Duncan 1955; Cortese, Falk, and Cohen 1976, 1978; James and Taeuber 1985; Massey and Denton 1988; Hutchens 2004). *Evenness* refers to actual equality across units: if firms have 10 employees and if there are as many men as women in the working population, evenness occurs if there are exactly five men and five women in each firm. *Random allocation* implies that the *probabilities* for a given individual to be a woman (or a man) are equal in all firms, even if strict equality in actual *proportions* is not reached. This article presents a measure from randomness rather than evenness, as the former benchmark is interesting to many practitioners.

2.1 Statistical Framework

The population is assumed to be split into two groups, a minority group and the rest of the population, and to be distributed across A units, $a = 1, \dots, A$. In practice, groups may be defined according to gender, nationality, ethnicity, or social status, while units may be businesses, schools, or neighborhoods. In the present analysis, the number of individuals in unit a , denoted as M_a , is drawn from a given, unknown distribution. In the whole analysis, A is assumed to be large, while M_a is assumed to be small.

Let p_a denote the probability for an individual of unit a to be a member of the minority group. The random variables p_a , that take values in $[0, 1]$, are assumed iid in distribution F . The number N_a of individuals in unit a that belong to the minority is observed and distributed as a Binomial(M_a, p_a). While N_a and M_a are perfectly observed, p_a is not. The observed sample proportion $\pi_a = N_a/M_a$ of the minority group in unit a is usually used to estimate p_a . If the number M_a of individuals in unit a goes to infinity, π_a is a consistent estimator of p_a ; furthermore, $\mathbb{E}[\pi_a | p_a] = p_a$, so that it is also an unbiased estimator.

2.2 Evenness, Randomness, and the Index of Interest

Segregation indices measuring distance from evenness can be defined as functions of a vector of proportions $\{\pi_a\}_{a=1, \dots, A}$: let \tilde{I} denote these “direct indices.” Let $\bar{p} = \sum_a N_a / \sum_a M_a$ denote the sample mean; note that \bar{p} is an unbiased estimator of $\mathbb{E}(p)$ whatever the unit size. Three indices are used in this article—the Gini index, the dissimilarity (or Duncan) index, and the Theil index (see, for instance, Massey and Denton 1988, for a review of the properties of these indices)—but the analysis can be generalized to any concentration index. Defining $w_a = M_a / \sum_{a'} M_{a'}$ as the weight of unit a in the sample, the direct versions of these indices, in the two-group case, can be

expressed as

$$\tilde{G} = \frac{1}{2\bar{p}(1-\bar{p})} \sum_a \sum_{a'} w_a w_{a'} \pi_a (1 - \pi_{a'}),$$

$$\tilde{D} = \frac{1}{2\bar{p}(1-\bar{p})} \sum_a w_a |\pi_a - \bar{p}|,$$

$$\tilde{H} = 1 - \sum_a w_a \frac{\pi_a \log \pi_a + (1 - \pi_a) \log(1 - \pi_a)}{\bar{p} \log \bar{p} + (1 - \bar{p}) \log(1 - \bar{p})}.$$

The random-allocation value I^* is defined as the expectation of \tilde{I} , conditional on all units being assigned the same probability $p_a = \mu$. When the probabilities of all units are equal to μ (a distribution denoted as \mathcal{D}_μ), the unevenness is entirely due to random allocation and $\mathbb{E}(\tilde{I}) = I^*$. To measure the distance to randomness, the index of interest should not be computed with the proportions π_a but with the unobserved probabilities p_a . The expectation of the index based on the probabilities p_a depends on the distribution F and is therefore denoted as $I(F)$. For the Gini, the dissimilarity, and the Theil indices, the expressions as functionals of F are the following (see the online Appendix for details):

$$G(F) = \frac{1 - \mathbb{E}(p) - \int_0^1 F^2}{\mathbb{E}(p)(1 - \mathbb{E}(p))}, \quad (1)$$

$$D(F) = \frac{\int_0^1 |p - \mathbb{E}(p)| dF(p)}{2\mathbb{E}(p)(1 - \mathbb{E}(p))}, \quad (2)$$

$$H(F) = 1 - \frac{\int_0^1 p \log p dF(p) + \int_0^1 (1 - p) \log(1 - p) dF(p)}{\mathbb{E}(p) \log \mathbb{E}(p) + (1 - \mathbb{E}(p)) \log(1 - \mathbb{E}(p))}. \quad (3)$$

M_a being small, π_a are going to be noisy estimates of p_a and direct indices \tilde{I} biased estimates of $I(F)$. The expected small-unit bias is defined as the difference between $\mathbb{E}(\tilde{I})$ and $I(F)$.

How large is the bias in practice? Cortese, Falk, and Cohen (1976) and CT ran simulations that showed how relevant the issue is; I reproduce these simulations for the dissimilarity index (the setting and the results are presented in the online Appendix). Two conclusions can be drawn from this exercise. First, the magnitude of the bias, around 0.5 for units of 15 people and a minority proportion of 5%, makes it an issue one cannot neglect. Second, the bias decreases with the unit size and with the total share of the minority group.

2.3 Existing Methods

CT propose a measure of the departure from randomness, based on the Euclidean distance between \tilde{I} and \hat{I}^* , a simulation-based estimate of I^* :

$$I_{CT} \doteq \frac{\tilde{I} - \hat{I}^*}{1 - \hat{I}^*}.$$

As CT do not make any assumption about the data-generating process (dgp) of (N_a, M_a) , there is no reason why I_{CT} would converge to $I(F)$. Still, $\mathbb{E}(I_{CT})$ happens to coincide with $I(F)$ in some cases. When the distribution of p_a is \mathcal{D}_μ , $\mathbb{E}(I_{CT}) = I(F) = 0$. When, conversely, $p_a = 1$ in some units while $p_a = 0$ in all the others (a distribution denoted as $\mathcal{D}_{0,1}(\mu)$, where μ is the

weight on value 1), $\tilde{I} = I_{CT} = 1 = I(F)$ for all samples. For every concave mixture between the discrete distributions \mathcal{D}_μ and $\mathcal{D}_{0,1}(\mu)$ (denoted as $\mathcal{D}_{0,\mu,1}(w)$, where w is the weight on the distribution \mathcal{D}_μ), it can be proved that $\mathbb{E}(I_{CT}) = I(F)$.

More precisely, three conclusions can be established for the Theil and the dissimilarity indices (see the online Appendix for a formal proof). First, when the true distribution is one of the family $\mathcal{D}_{0,\mu,1}(w)$, the CT adjustment leads to $I(F)$: $\mathbb{E}(I_{CT}) = I(F)$. For the dissimilarity index, this implication turns out to be an equivalence. For every other distribution, continuous or discrete, the CT adjustment leads, on average, to a lower value than $D(F)$: $\mathbb{E}(D_{CT}) < D(F)$. Finally, for the Theil index, there is no such property. The difference between H_{CT} and $H(F)$ may be positive or negative, depending on the distribution.

ABW proposed to use bootstrap techniques to adjust the index for the presence of a potential bias. Given the unit size M_a and the observed proportions π_a , they simulate B samples, drawing $N_a(b)$, $b = 1, \dots, B$. For each simulated sample b , an index $\tilde{I}(b)$ is computed. The corrected index they proposed is then

$$I_{ABW} \doteq 2\tilde{I} - \frac{1}{B} \sum_{b=1}^B \tilde{I}(b).$$

Their idea is that $\tilde{I} - \frac{1}{B} \sum_{b=1}^B \tilde{I}(b)$ is an estimator for the small-unit bias and that adding it to \tilde{I} provides an estimator for the unbiased estimator. This strategy succeeds in reducing the order of the bias from $O(1/M)$ to $O(1/M^{3/2})$ or even $O(1/M^2)$.

Section 4 proposes simulations to assess whether the adjusted indices proposed by CT and ABW fall close to or far from $I(F)$.

3. A PARAMETRIC METHOD

Unlike existing methods, this article proposes a correction method based on a parametric assumption: p_a is distributed as a mixture of Beta distributions. Since its formalization by Skellam (1948), the *Beta-binomial* model has been used in various fields (e.g., Lee and Sabavala 1987; Cox and Katz 1999; Cogley and Sargent 2009) and has three main virtues. First, the Beta distribution is the conjugate prior of the binomial distribution (Greenwood 1913). Second, the model is parsimonious: $3c - 1$ parameters are enough to describe a c -component mixture of Beta distributions. Third, Beta distributions encompass many different cases.

One may object that a parametric approach may lead to invalid results when the model is misspecified. Two arguments can be used to support this approach. First, Diaconis and Ylvisaker (1985, Theorem 1) pointed out that c -component mixtures of Beta distributions are dense in the space of the continuous distributions on the unit interval. Second, in the present case, the results of simulations with various dgp show that, using mixtures with at most two components, the segregation indices corresponding to both continuous and discrete distributions are accurately proxied by the mixtures (see Section 4).

Let $B(\cdot, \cdot)$ denote the Beta function, $v = \{\alpha_j, \beta_j, \lambda_j\}_{j \in \{1, \dots, c\}}$ the vector of parameters with $\sum_j \lambda_j = 1$. The pdf of the rv p_a , distributed as a c -component mixture of Beta distributions, is

$$f_v(p) \doteq f(p; \{\alpha_j, \beta_j, \lambda_j\}_{j \in \{1, \dots, c\}}) = \sum_{j=1}^c \lambda_j \frac{p^{\alpha_j-1} (1-p)^{\beta_j-1}}{B(\alpha_j, \beta_j)}.$$

The probability that n individuals out of m belong to the minority group can be written, after some algebra, as

$$\mathbb{P}(N_a = n | M_a = m) = \binom{m}{n} \sum_{j=1}^c \lambda_j \frac{B(\alpha_j + n, \beta_j + m - n)}{B(\alpha_j, \beta_j)}. \quad (4)$$

Conditional on the unit size M_a , the probability expressed in Equation (4) is the likelihood that a unit a will contain N_a persons from the minority population out of a total of M_a . Let A_m^n denote the number of units of size m with n minority individuals; the log-likelihood may be written as

$$\ell_m(v) = \sum_{n=0}^m A_m^n \log \sum_{j=0}^c \lambda_j \frac{B(\alpha_j + n, \beta_j + m - n)}{B(\alpha_j, \beta_j)}. \quad (5)$$

Assuming that the same model holds for a set of units of size belonging to $\mathcal{M} = \{m_1, \dots, m_r\}$, maximizing $\ell_{\mathcal{M}}(v) = \sum_{m \in \mathcal{M}} \ell_m(v)$ with respect to v provides the estimators $\hat{v}(\mathcal{M})$. In other words, instead of stratifying the sample by unit size, units of different sizes can be pooled in the same estimation. The set \mathcal{M} should be chosen by the practitioner, depending on the situation, from singleton sets to the entire support of the distribution of the unit size.

Once the parameters of the distribution are known, indices could be retrieved by simulations. However, in the case of this model, explicit expressions of the indices can be derived, to save computational time. The Gini, the dissimilarity, and the Theil indices admit the following expressions, as functions of the vector of parameters v (see the online Appendix for details):

$$\begin{aligned} G(v) &= 1 - \frac{2}{\mu(v)(1 - \mu(v))} \\ &\times \int_0^1 \left(\sum_{j=1}^c \frac{\lambda_j \beta_j}{\alpha_j + \beta_j} f(p; \alpha_j, \beta_j + 1) \right) \\ &\times \left(\sum_{j=1}^c \frac{\lambda_j \alpha_j}{\alpha_j + \beta_j} I(p; \alpha_j + 1, \beta_j) \right) dp, \end{aligned} \quad (6)$$

$$\begin{aligned} D(v) &= \sum_{j=1}^c \frac{\lambda_j}{\alpha_j + \beta_j} \left[\frac{\beta_j}{1 - \mu(v)} I(\mu(v); \alpha_j, \beta_j + 1) \right. \\ &\quad \left. - \frac{\alpha_j}{\mu(v)} I(\mu(v); \alpha_j + 1, \beta_j) \right], \end{aligned} \quad (7)$$

$$\begin{aligned} H(v) &= 1 - \left(\sum_{j=1}^c \lambda_j [\alpha_j \psi(\alpha_j + 1) + \beta_j \psi(\beta_j + 1) \right. \\ &\quad \left. - (\alpha_j + \beta_j) \psi(\alpha_j + \beta_j + 1)] \right) / \left(\mu(v) \log(\mu(v)) \right. \\ &\quad \left. + (1 - \mu(v)) \log(1 - \mu(v)) \right), \end{aligned} \quad (8)$$

where $\psi(\cdot)$ is the digamma function, $I(\cdot, \alpha, \beta)$ the regularized incomplete Beta function, and $\mu(v) = \sum_j \lambda_j \frac{\alpha_j}{\alpha_j + \beta_j}$. Note that the expressions of $D(v)$ and $H(v)$ are closed forms while $G(v)$

involves an integral that must be approximated by numerical methods.

Two methods may be used to provide inference on the indices based on the estimated values \hat{v} of the parameters. The delta method is easy to apply in this context as it only involves an estimate of the variance matrix of \hat{v} and of the derivative of the index with respect to v , evaluated at \hat{v} . The former is computed using the Hessian matrix, evaluated at \hat{v} , and the latter can be computed either analytically starting from Equations (6) to (8) or numerically, at little computational cost. The bootstrap, performed at the level of the units, can also be used. Both methods provide very similar results in the simulations exercise and in the application; for the sake of readability, only the results of the delta method are reported.

Finally, how should the number of components of the mixture model be chosen? Given the estimation of the model for $c - 1$ and c components, a likelihood-ratio test can be used iteratively to test whether the likelihood improvement is worth spending three additional degrees of freedom and which model should be preferred. Other methods of choosing c could also be used.

4. SIMULATIONS

As practitioners do not know a priori the distribution of p_a , they expect bias-adjusting methods to work on the largest possible spectrum. In this section, simulations using several continuous and discrete distributions are run to assess the performance of the method presented in this article, and to compare it to the solutions presented in CT and ABW. The unit size is fixed to 10 (in the online Appendix, simulations with a unit size of five are also presented). For each unit size and each distribution, 100 draws in 1000 units are made. First p_a is drawn iid in the given distribution. Then, N_a is drawn from a binomial with parameters M_a , p_a . Table 1 displays the average values of the estimates, as well as 95% confidence intervals. Table 2 displays (100 times) their mean-squared errors (MSE), computed as the mean of the squared differences between the estimate and the value of the index based on probabilities p_a . Each panel of the tables is dedicated to a given index; the distributions of the dgp are in rows and the methods in columns.

In both tables, the first column presents the result for the direct estimates, computed with proportions π_a . Columns 2–4 show the values obtained with the Beta-parametric method, assuming either a simple Beta model (column 2) or a mixture of two Beta distributions (column 3). In the fourth column, the best model (between Beta-1 and Beta-2) is chosen according to the result of a LR test, using a threshold of 0.05 for the p -value. In columns 5 and 6, the values relating to indices adjusted using CT and ABW methods are reported. In Table 1, the unfeasible estimate is also reported, to make comparisons easier.

Seven dgps of expectation 0.1 are tested. For B_1 , the dgp is a Beta distribution of parameters (1, 9). For B_2 , the dgp is a mixture of two Beta distributions of parameters (1, 9) and (0.1, 0.9) with weights (0.7, 0.3). For D_1 , the dgp is a discrete distribution of support set (0, 0.1, 1) with associated weights (0.45, 0.5, 0.05). For D_2 , the dgp is a discrete distribution of support set (0.05, 0.1, 0.5) with associated weights (0.45, 0.5, 0.05). For D_3 , the dgp is a discrete distribution of support set (0, 0.05, 0.1, 0.15, 0.2) with associated weights (0.2, 0.2, 0.2, 0.2, 0.2). For N , the dgp is a truncated normal distribution of mean

0.1 and standard deviation 0.05. For W , the dgp is a truncated Weibull distribution of parameters 0.1 and 1.1. Note that in all but the first two dgp, the Beta-binomial model is misspecified.

Consistently with earlier results, direct indices are found to suffer from large biases. Despite their imperfections, adjusting methods improve on the direct estimates in most cases. The comparison of the last five columns underlines the advantages and drawbacks of each method. As established in Section 2, the CT-adjusted dissimilarity index is always lower than $D(F)$, except when the true distribution is a $\mathcal{D}_{0.1,1}$; interestingly, this seems to be also true for the Gini index. In many cases, for the Gini and the dissimilarity indices, the differences between the CT-adjusted indices and $I(F)$ are of large magnitude, for example, 0.07 versus 0.21 with a truncated normal. Conversely, the CT adjustment almost coincides with $I(F)$ for the Theil index. The indices corrected by the ABW method are upward biased in most cases. Their method performs better when the unfeasible index is high and when the distribution is continuous. For the Theil index, the ABW method is relatively less efficient than the other methods.

The Beta-1 correction, based on the assumption of a Beta distribution, is obviously at its best when the data are drawn from a Beta distribution. If the Normal, the Weibull, and even the discrete distribution with 5 support points are also satisfactorily dealt with, the discrete distributions with 3 support points lead to substantially higher MSE for the Gini and the dissimilarity indices. The Beta-2 correction improves on Beta-1 in the latter cases. The largest MSE (0.0063) of this method is obtained for the dissimilarity index with the $\mathcal{D}_{0.1,1}$ distribution, a value of the same magnitude as the MSEs experienced by the other methods in many cases. The Beta correction lies between Beta-1 and Beta-2: it allows flexibility when necessary while avoiding systematically overparameterizing the model.

Table 3 sums up the results of the simulations. For each dgp and index, the table reports the method that leads to the estimator with the lowest MSE. When another method leads to a MSE lower than 0.001, it is reported in the second position. A rapid glance at the table shows that the Beta-mixture method is the one that gives, in most cases, the closest estimates to $I(F)$. The only case in which the parametric method does not score best is the dissimilarity index with the discrete distributions $\mathcal{D}_{0.1,1}$.

5. APPLICATION

This section provides a first attempt to measure ethnic residential segregation in France. As it is forbidden by law to collect race or ethnicity variables in France, the usual way to proxy ethnicity is to use parents' nationality at birth (see, e.g., Meurs, Pailhé, and Simon 2006; Aeberhardt et al. 2010). Unfortunately, while Censuses provide many variables (social and labor situations, education, etc.) at the scale of the neighborhood, parents' nationalities remain absent from this file, for legal reasons. The largest dataset in which parents' nationalities are observed, since 2005, is the Labor Force Survey (LFS).

The sample design of the LFS defines ad hoc neighborhoods. Households are selected through a three-fold geographical cluster sampling. The smallest clusters are the *sampling units* (named “aires”) and have, on average, 20 contiguous households. Households of a given sampling unit enter and leave the sample on the same quarter. The LFS dataset provides, for each

Table 1. Simulations: estimates with units of 10 individuals

	Unfeasible	Direct	Beta-1	Beta-2	Beta	CT	ABW
Gini							
B_1	0.53 (0.51–0.54)	0.70 (0.68–0.72)	0.53 (0.48–0.56)	0.52 (0.47–0.56)	0.52 (0.48–0.56)	0.33 (0.29–0.38)	0.61 (0.58–0.64)
B_2	0.69 (0.67–0.71)	0.80 (0.78–0.82)	0.71 (0.67–0.74)	0.69 (0.66–0.73)	0.69 (0.66–0.73)	0.54 (0.49–0.59)	0.74 (0.72–0.77)
D_1	0.75 (0.71–0.78)	0.89 (0.87–0.91)	0.87 (0.84–0.89)	0.77 (0.72–0.81)	0.77 (0.72–0.81)	0.75 (0.70–0.80)	0.85 (0.82–0.87)
D_2	0.36 (0.33–0.39)	0.69 (0.66–0.71)	0.50 (0.45–0.54)	0.34 (0.25–0.46)	0.34 (0.25–0.46)	0.28 (0.23–0.34)	0.57 (0.54–0.61)
D_3	0.44 (0.42–0.46)	0.67 (0.65–0.70)	0.45 (0.39–0.49)	0.43 (0.38–0.50)	0.43 (0.38–0.50)	0.25 (0.20–0.29)	0.56 (0.53–0.60)
N	0.29 (0.28–0.30)	0.60 (0.58–0.62)	0.28 (0.22–0.34)	0.26 (0.17–0.33)	0.28 (0.21–0.34)	0.11 (0.06–0.16)	0.46 (0.43–0.49)
W	0.51 (0.50–0.53)	0.70 (0.68–0.73)	0.52 (0.47–0.56)	0.50 (0.45–0.56)	0.52 (0.47–0.56)	0.32 (0.27–0.37)	0.61 (0.58–0.64)
Dissimilarity							
B_1	0.39 (0.37–0.40)	0.53 (0.50–0.55)	0.39 (0.35–0.42)	0.39 (0.34–0.43)	0.39 (0.35–0.42)	0.22 (0.19–0.26)	0.41 (0.37–0.44)
B_2	0.51 (0.49–0.53)	0.64 (0.61–0.66)	0.54 (0.51–0.58)	0.52 (0.49–0.55)	0.52 (0.49–0.56)	0.37 (0.34–0.42)	0.54 (0.51–0.58)
D_1	0.51 (0.47–0.56)	0.70 (0.67–0.72)	0.72 (0.69–0.75)	0.59 (0.54–0.63)	0.59 (0.54–0.63)	0.50 (0.45–0.54)	0.61 (0.57–0.65)
D_2	0.25 (0.23–0.28)	0.49 (0.47–0.52)	0.36 (0.33–0.40)	0.27 (0.21–0.33)	0.27 (0.21–0.33)	0.15 (0.12–0.19)	0.35 (0.31–0.39)
D_3	0.34 (0.32–0.35)	0.51 (0.49–0.54)	0.32 (0.28–0.36)	0.36 (0.28–0.41)	0.35 (0.28–0.41)	0.18 (0.14–0.22)	0.38 (0.35–0.42)
N	0.21 (0.20–0.22)	0.43 (0.42–0.46)	0.20 (0.16–0.24)	0.20 (0.13–0.27)	0.20 (0.14–0.25)	0.07 (0.03–0.11)	0.28 (0.25–0.32)
W	0.38 (0.36–0.39)	0.53 (0.51–0.56)	0.38 (0.34–0.42)	0.37 (0.31–0.43)	0.38 (0.34–0.42)	0.21 (0.18–0.25)	0.41 (0.37–0.45)
Theil							
B_1	0.13 (0.12–0.14)	0.28 (0.26–0.30)	0.13 (0.11–0.15)	0.13 (0.11–0.15)	0.13 (0.11–0.15)	0.12 (0.10–0.14)	0.19 (0.17–0.21)
B_2	0.26 (0.23–0.29)	0.38 (0.36–0.41)	0.25 (0.22–0.29)	0.25 (0.22–0.29)	0.25 (0.22–0.29)	0.24 (0.20–0.28)	0.31 (0.27–0.34)
D_1	0.50 (0.46–0.54)	0.59 (0.55–0.63)	0.47 (0.43–0.52)	0.47 (0.42–0.52)	0.47 (0.42–0.52)	0.50 (0.45–0.55)	0.53 (0.49–0.58)
D_2	0.10 (0.09–0.12)	0.27 (0.26–0.29)	0.11 (0.09–0.14)	0.10 (0.08–0.13)	0.10 (0.08–0.13)	0.11 (0.09–0.14)	0.17 (0.15–0.20)
D_3	0.11 (0.10–0.12)	0.25 (0.24–0.27)	0.09 (0.07–0.11)	0.11 (0.09–0.13)	0.10 (0.07–0.13)	0.08 (0.06–0.10)	0.15 (0.13–0.17)
N	0.04 (0.04–0.04)	0.21 (0.19–0.22)	0.04 (0.02–0.05)	0.04 (0.02–0.06)	0.04 (0.02–0.05)	0.04 (0.02–0.05)	0.10 (0.08–0.12)
W	0.12 (0.12–0.13)	0.28 (0.26–0.30)	0.12 (0.10–0.15)	0.12 (0.10–0.15)	0.12 (0.10–0.15)	0.12 (0.09–0.14)	0.18 (0.16–0.21)

NOTE: For each distribution, simulations are based on 100 draws of samples of 1000 areal units, each consisting of 10 individuals. 95% confidence interval are showed in parentheses. For B_1 , the dgp is a Beta distribution of parameters (1, 9). For B_2 , the dgp is a mixture of 2 Beta distribution of parameters (1, 9) and (0.1, 0.9) with weights (0.7, 0.3). For D_1 , the dgp is a discrete distribution of support set (0, 0.1, 1) with associated weights (0.45, 0.5, 0.05). For D_2 , the dgp is a discrete distribution of support set (0.05, 0.1, 0.5) with associated weights (0.45, 0.5, 0.05). For D_3 , the dgp is a discrete distribution of support set (0, 0.05, 0.1, 0.15, 0.2) with associated weights (0.2, 0.2, 0.2, 0.2, 0.2). For N , the dgp is a truncated normal distribution of mean 0.1 and standard deviation 0.05. For W , the dgp is a truncated Weibull distribution of parameters 0.1 and 1.1.

Source: Simulations by the author.

individual, an encrypted version of the ID of their sampling unit: the researcher knows whether two individuals live in the same unit, but not the unit's location.

The mean size of a sampling unit is 30; the median is 31; 25% of the sampling units are smaller than 20 and 91% smaller than 50 (see the online Appendix for the complete distribution). Maurin (2004) used the LFS to obtain concentration measures

of social status and ethnicity but, because of the small-unit issue, did not use the usual indices. Small-unit issues are likely to be aggravated by the relative scarcity of ethnic minorities compared to French individuals of French origin. A complementary analysis conducted at an aggregated level shows that small-unit issues are not negligible, even with unit sizes around 100, when the minority share is below 5% (see Rathelot 2011, for details).

Table 2. Simulations: mean-squared errors ($\times 100$) with units of 10 individuals

	Direct	Beta-1	Beta-2	Beta	CT	ABW
Gini						
B_1	3.22	0.03	0.06	0.04	3.70	0.72
B_2	1.31	0.04	0.02	0.02	2.32	0.30
D_1	1.98	1.51	0.07	0.07	0.02	0.97
D_2	10.85	2.00	0.37	0.37	0.61	4.63
D_3	5.05	0.05	0.13	0.12	3.77	1.34
N	9.71	0.10	0.27	0.13	3.28	2.88
W	3.61	0.05	0.10	0.06	3.74	0.87
Dissimilarity						
B_1	2.06	0.02	0.05	0.03	2.74	0.08
B_2	1.51	0.10	0.02	0.03	2.13	0.12
D_1	3.53	4.40	0.63	0.63	0.04	1.05
D_2	6.12	1.44	0.11	0.11	0.93	1.05
D_3	2.93	0.04	0.15	0.12	2.39	0.25
N	5.18	0.05	0.15	0.06	1.88	0.58
W	2.37	0.04	0.08	0.04	2.72	0.12
Theil						
B_1	2.24	0.01	0.01	0.01	0.02	0.33
B_2	1.66	0.01	0.01	0.01	0.04	0.26
D_1	0.84	0.08	0.08	0.08	0.01	0.12
D_2	2.92	0.02	0.01	0.01	0.02	0.51
D_3	1.96	0.05	0.02	0.03	0.07	0.20
N	2.80	0.01	0.01	0.01	0.01	0.36
W	2.38	0.01	0.02	0.01	0.02	0.37

NOTE: For each distribution, simulations are based on 100 draws of samples of 1000 areal units, each consisting of 10 individuals. For the sake of clarity, values in the table are actually 100 times the MSE. For B_1 , the dgp is a Beta distribution of parameters (1, 9). For B_2 , the dgp is a mixture of 2 Beta distribution of parameters (1, 9) and (0.1, 0.9) with weights (0.7, 0.3). For D_1 , the dgp is a discrete distribution of support set (0, 0.1, 1) with associated weights (0.45, 0.5, 0.05). For D_2 , the dgp is a discrete distribution of support set (0.05, 0.1, 0.5) with associated weights (0.45, 0.5, 0.05). For D_3 , the dgp is a discrete distribution of support set (0, 0.05, 0.1, 0.15, 0.2) with associated weights (0.2, 0.2, 0.2, 0.2, 0.2). For N , the dgp is a truncated normal distribution of mean 0.1 and standard deviation 0.05. For W , the dgp is a truncated Weibull distribution of parameters 0.1 and 1.1.

Source: Simulations by the author.

The Beta-binomial adjusting method is applied to the LFS from 2005 to 2008 for the shares of ethnic minorities within sampling units, on three populations. The first population are all individuals with foreign parents, whether they are themselves immigrants or not. The second population (“immigrants”) is a subsample of the first one, with only the immigrants who arrived in France after the age of 3. The third population (“French-born”) is the complement of the second population: only those

Table 3. Simulations: which method should be preferred in which case

	Gini	Dissimilarity	Theil
B_1	Beta	Beta, ABW	Beta, CT
B_2	Beta	Beta	Beta, CT
D_1	CT, Beta	CT	CT, Beta
D_2	Beta	Beta	Beta, CT
D_3	Beta	Beta	Beta, CT
N	Beta	Beta	Beta, CT
W	Beta	Beta	Beta, CT

NOTE: This table is a summary of Table 1. For each distribution and each index, the least-biased method is reported. If other methods provide estimates with a $100 \times \text{MSE}$ lower than 0.10, they appear in second (and third if necessary) positions. For B_1 , the dgp is a Beta distribution of parameters (1, 9). For B_2 , the dgp is a mixture of 2 Beta distribution of parameters (1, 9) and (0.1, 0.9) with weights (0.3, 0.7). For D_1 , the dgp is a discrete distribution of support set (0, 0.1, 1) with associated weights (0.45, 0.5, 0.05). For D_2 , the dgp is a discrete distribution of support set (0.05, 0.1, 0.5) with associated weights (0.45, 0.5, 0.05). For D_3 , the dgp is a discrete distribution of support set (0, 0.05, 0.1, 0.15, 0.2) with associated weights (0.2, 0.2, 0.2, 0.2, 0.2). For N , the dgp is a truncated normal distribution of mean 0.1 and standard deviation 0.05. For W , the dgp is a truncated Weibull distribution of parameters 0.1 and 1.1.

Source: Simulations by the author.

individuals born in France or who arrived before the age of 3. Minority groups (“Sub-Saharan Africa,” “North Africa,” “Middle East,” “Southern Europe,” “Northern Europe,” “Eastern Europe,” and “Asia”) are defined according to parents’ nationalities (at least one of them). Individuals from “Northern Europe,” “Eastern Europe,” and “Asia” are required to have at least one parent of the corresponding nationality. For each minority group, the sample size and the proportion in the whole population are reported in Table 4. Individuals with parents from North Africa and Southern Europe are by far the most common. Together, they represent more than 10% of the population living in France; half of them are immigrant and half were born in France.

The results for the dissimilarity index are reported in Table 5 (see the online Appendix for the Gini and the Theil). Columns 1 and 2 present the results on the whole population, columns 3 and 4 on the immigrant sample, and columns 5 and 6 on the French-born sample. For each population, the first column presents the index computed with the Beta method and the second one the index computed directly using sample proportions. As noted above, direct indices differ dramatically from the Beta-adjusted ones.

This application provides an interesting example of how useful accounting for the small-unit issue is. For all ethnic groups

Table 4. Sample size and proportions of the main ethnic minorities in France

Parents’ nationalities	Whole sample		Immigrant sample		French-born sample	
	Sample size	Proportion	Sample size	Proportion	Sample size	Proportion
<i>Sub-Saharan Africa</i>	2474	0.8%	1765	0.6%	709	0.2%
<i>North Africa</i>	14826	4.8%	8528	2.7%	6298	2.0%
<i>Middle East</i>	4462	1.4%	3302	1.1%	1160	0.4%
<i>Southern Europe</i>	18335	5.9%	6841	2.2%	11494	3.7%
<i>Northern Europe</i>	5970	1.9%	2388	0.8%	3582	1.2%
<i>Eastern Europe</i>	4659	1.5%	1917	0.6%	2742	0.9%
<i>Asia</i>	1173	0.4%	692	0.2%	481	0.2%

NOTE: Columns 1, 3, and 5 report sample size; columns 2, 4, and 6 report proportions with respect to the total sample (representative of individuals of more than 16 living in France).

Source: Labor Force Survey 2005–2008 (Insee).

Table 5. Segregation indices, by parents' nationalities

Parents' nationalities	Dissimilarity					
	Whole sample		Immigrant sample		French-born sample	
	Beta	Direct	Beta	Direct	Beta	Direct
<i>Sub-Saharan Africa</i>	0.75 (0.73–0.76)	0.87 (0.87–0.88)	0.83 (0.81–0.86)	0.91 (0.90–0.91)	0.73 (0.70–0.76)	0.94 (0.94–0.95)
<i>North Africa</i>	0.59 (0.58–0.60)	0.65 (0.65–0.66)	0.66 (0.65–0.67)	0.73 (0.72–0.74)	0.53 (0.52–0.55)	0.68 (0.68–0.69)
<i>Middle East</i>	0.68 (0.67–0.70)	0.81 (0.80–0.82)	0.73 (0.72–0.74)	0.85 (0.84–0.86)	0.72 (0.70–0.75)	0.92 (0.91–0.92)
<i>Southern Europe</i>	0.38 (0.37–0.38)	0.47 (0.46–0.48)	0.50 (0.49–0.51)	0.65 (0.64–0.66)	0.35 (0.34–0.36)	0.49 (0.48–0.50)
<i>Northern Europe</i>	0.40 (0.38–0.42)	0.63 (0.62–0.63)	0.59 (0.56–0.62)	0.84 (0.83–0.85)	0.35 (0.31–0.38)	0.71 (0.70–0.72)
<i>Eastern Europe</i>	0.46 (0.45–0.48)	0.69 (0.68–0.70)	0.64 (0.62–0.67)	0.87 (0.86–0.88)	0.43 (0.41–0.45)	0.77 (0.76–0.78)
<i>Asia</i>	0.80 (0.77–0.83)	0.92 (0.91–0.93)	0.85 (0.83–0.87)	0.95 (0.95–0.96)	0.69 (0.65–0.74)	0.96 (0.95–0.96)

NOTE: Segregation is measured at the level of the sampling unit of the LFS. The first three columns present the indices computed after the estimation of the Beta model. The last three columns present the indices directly computed with the observed proportions. Confidence intervals at the level of 5% are displayed in parentheses.

Source: Labor Force Survey 2005–2008 (Insee).

but Europeans, the proportion of immigrants is higher than the proportion of French-born individuals. In the case of Africa and Asia, for instance, the direct index that measures the distance to evenness is higher in the French-born group than in the immigrant one while the Beta index gives the opposite ranking. Accounting for small units also enables one to compare ethnic groups with each other, even when some groups are more frequent than others. According to direct indices, immigrants from Northern Europe are more segregated than those from North Africa; the Beta indices lead to the opposite result.

Finally, two groups may be distinguished in the whole sample: those with European parents are the least segregated, while those with African or Middle Eastern parents are the most segregated. For the French-born group, this ranking is not much different; the values are smaller but are more contrasted. The least segregated individuals are those with parents from Southern and Northern Europe, while individuals with parents from Asia, the Middle East, and Sub-Saharan Africa are the most segregated group. Focusing on immigrants, indices are substantially higher and closer to each other and the ranking changes marginally. Immigrants from Southern Europe are the least segregated while those from Sub-Saharan Africa and Asia are the most segregated.

6. CONCLUSION

When units (neighborhoods, businesses, classrooms) have few observations, the standard indices, which measure a distance to evenness, are not relevant: the desirable benchmark is randomness. The small-unit issue occurs because standard indices use minority shares to proxy the true probabilities that an individual of the unit belongs to the minority group. This article presents a statistical framework that provides a natural way to define the index of interest: the unfeasible one that would be based on these true unobserved probabilities instead of esti-

mated shares. A new method is proposed to estimate this index of interest. Assuming that the distribution of the probabilities is a mixture of Beta distributions, the parameters of the distribution can be estimated, and segregation indices deduced.

This new method is compared to the two main existing methods, introduced by Carrington and Troske (1997) and Allen, Burgess, and Windmeijer (2009), using simulations. In most cases, which are not restricted to data-generating processes distributed as Beta mixtures, the new method is shown to fall closer to the quantity of interest. One should stress, however, that Carrington and Troske (1997) did not claim to estimate the same quantity of interest, so that the differences between their adjusted index and our quantity of interest cannot be interpreted as bias. An application provides the first available figures about ethnic residential segregation in France, using the LFS and its unique sampling scheme to define neighborhoods. French individuals whose parents are immigrants experience levels of residential segregation that vary much across countries of origin. Individuals with parents from Sub-Saharan Africa, the Middle East, and North Africa experience higher levels of residential concentration than those with parents coming from Europe.

Several extensions of the present method would be useful for practitioners. First, when covariates X are observed for individuals (and units), the practitioner might wish to measure to what extent segregation can be attributed by differences in covariates between the minority and majority groups (e.g., Hellerstein and Neumark 2008; Aslund and Skans 2009). This extension could be done nonparametrically, by stratifying the analysis between the different values of the observables, or parametrically, to avoid the curse of dimensionality. Second, in some analyses, it is useful to account for the presence of more than two groups, and to compute multigroup segregation indices. The approach proposed in this article could, in principle, be extended to the case of multigroup indices by assuming a Dirichlet-multinomial model instead of a Beta-binomial one.

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