RETHINKING GENDER SEGREGATION AND GENDER INEQUALITY: MEASURES AND MEANINGS*

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It is often assumed that occupational segregation by gender is readily interpretable as an index of inequality between men and women in the labor force. Although this view has been challenged, the development and dissemination of analytic tools that could test this assumption have been limited. This article reviews two methods for identifying invidious and noninvidious components of gender segregation and develops a third approach that overcomes some limitations of the other two. Each method is applied to a data set that consists of observations from 22 countries covered in the International Social Survey Program. The results are compared and contrasted, and several conclusions emerge. First, occupational segregation is not completely interpretable as occupational gender inequality. Second, the methods differ in how large they estimate the invidious (vertical) component to be. Third, each method produces measures of invidious and noninvidious segregation that can be predicted statistically from other characteristics of the countries in question. The article ends with suggestions about the circumstances under which the various approaches may be the most useful.

Although occupational segregation by gender is a widely studied phenomenon, there has been no resolution of one fundamental question regarding this form of social differentiation: whether occupational segregation is necessarily coterminous with occupational gender inequality. Social scientists, however, have expressed clear opinions on different sides of this issue. Consider the following statement from an intermediate-level text:

> Sex segregation matters for the same reason that the U.S. Supreme Court outlawed school segregation in 1964 [sic]: Among socially unequal groups, separate is not equal. Separating groups into different places and different roles makes it easier to treat them unequally, and it implies that treating them differently is acceptable. In contemporary societies, which use people's jobs to place them in the status system and distribute income and prestige, segregating the sexes into different jobs contributes to women's lower pay and lesser social power—at work, in their families, and in the larger society. (Reskin and Padovic 1994:46)

Social scientists have also been predisposed to conclude that segregation is tantamount to inequality by the extensive (and justified) attention given to sex segregation as a cause of women's lower earnings (see, for example, England 1992:44). But that literature is concerned with a different issue, namely, what proportion of the income gap is due to segregation. Even if the proportion were 100%, it would not address the issue of whether there is a noninvidious component of occupational gender segregation. That an overwhelming proportion of British citizens speak English, for example, does not mean that the majority of English speakers have British citizenship.

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There are also observers who have explicitly made the point that sex segregation does not always imply inequality:

> Frequently segregation, in the stricter, more narrow sense, is regarded as evidence of inequality, or even as directly measuring inequality. This is clearly not correct, as concentration of the sexes in different occupations does not necessarily mean that either is disadvantaged. (Blackburn and Jarman 1997:4; see also Blackburn, Brooks, and Jarman 2001:529)

Of course, the weight of evidence seems clearly on the side of those who have asserted, at least empirically, that gender segregation is associated with gender inequality. But several questions remain: how strong is this association?; does its strength vary across different social contexts?; assuming some variation, what might explain it?; and how do we interpret gender segregation that is *not* linked to inequality?

The premise of this article is that these questions can be answered only if there are measures of gender segregation that are adequate to the task. Therefore, the article has two explicit goals: (1) to reconsider two extant, but not very widely known, approaches to measuring segregation that distinguish inequality from noninequality components of segregation and assess their strengths and deficits, and (2) to propose a new segregation-measurement regime that overcomes many of their limitations. By applying these three measurement approaches to comparative, cross-sectional data on the labor force, I illustrate each technique and provide a vehicle for making comparisons among them.

Before I turn to these methods, however, I briefly review measures of segregation in general and recent developments in these endeavors—some of which have implications for the immediate project at hand. Next, I provide an introduction to the existing ways of decomposing segregation into inequality and noninequality components and present a derivation of the newly proposed methods and illustrate their calculation. Then, I apply these techniques to data on occupational segregation that were drawn from 22 societies, mostly in Europe, and compare them to other measures. Finally, I assess these techniques, suggest how they may be integrated into causal and other explanatory models, and speculate about their applicability to other forms of segregation.

MEASURES OF OCCUPATIONAL SEGREGATION

Recent Approaches

Until recently, the measurement of segregation, both residential and occupational, revolved around the Index of Dissimilarity (ID), an index that was popularized by Duncan and Duncan (1955). There have always been, of course, competing measures, including Theil's (1972) entropy-based index; Hakim's (1981, 1992) sex ratio index, used primarily by British researchers; and a number of others. Moreover, there have been numerous attempts to remedy widely acknowledged deficiencies in the ID, most notably its sensitivity to the marginal distribution of occupational categories (or areal units). Those who attempted to develop modifications include Gibbs (1965), who proposed a size-standardized ID; Cortese, Falk, and Cohen (1976), who developed a "standard score" version of ID; Blackburn, Siltanen, and Jarman (1995), who offered a measure called marginal matching that satisfies the criteria of "sex composition and gendered occupations invariance" (p. 325; also see Siltanen, Jarman, and Blackburn 1995); and the I_p index, developed by Karmel and MacLachlan (1988) and advocated by Watts (1998).[1]

1. The I_p index is a simple algebraic transformation of the ID, which, in its simplest form, is also sensitive to marginal distributions. Watts (1998) advocated decomposing this measure into a composition component and a "mix" component.

However, the most recent work in the measurement of occupational segregation has followed two separate paths. The first was the development by Reardon and Firebaugh (2002) of methods that allow segregation to be measured simultaneously among several population groups, overcoming the restriction of measures based on dichotomies, such as male-female or white-black. The second path has been pursued by those who have advocated log-linear techniques for the twin problems of measuring and explaining levels of occupational segregation by gender across countries (Charles 1992; Charles and Grusky 1995; Grusky and Charles 1998). This approach has allowed analysts to study occupational segregation, by definition a categorical phenomenon, with methods that are best suited for classified, as opposed to measured, variables. Another appealing feature of these methods is that they ground the measurement of segregation in the concept of odds ratios, providing a further integration of the analysis of segregation with the analysis of contingency tables more generally. One of their contributions, but hardly the most radical one, has been the derivation of two new segregation measures: the ratio index and the A index. Each of these is based on odds ratios and, therefore, enjoys the advantages and disadvantages of this approach.[2]

In another aspect, however, Grusky and Charles's (1998) methods depart more dramatically from conventional practice by steering analysts away from the conception of segregation as a unitary force operating throughout the occupational hierarchy and by pushing investigators toward the discovery of varying "segregation profiles" within countries. In their words, they "are uninterested in becoming yet another protagonist in the latest round of index wars" (Grusky and Charles 1998:498)—wars that, in their view, never overcome the fact "that qualitative differences in the segregation profile are ignored and emphasis is placed on simple differences in the degree of segregation" (p. 499). Essentially, the segregation profiles they proposed are line graphs in which a small number of discrete occupational categories are located on the x-axis, and a measure of the departure of each occupation category from the countries' "typical" gender composition is plotted on the y-axis. It is interesting that they discovered convergence or clustering of countries' profiles onto a small number of distinct patterns. However, a recent summary of their results captured the complexity that is inherent in conceiving of segregation as a collection of profiles: "the imagery that emerges is that of loosely coupled segregation systems cobbled together from many occupation specific solutions to the exigencies of modern industrial production and competing segregative and egalitarian cultural mandates" (Grusky and Charles 1998:504). This complexity is indubitably real, and the methods they proposed will likely contribute to the development of a theory that describes, organizes, and explains the multitude of profiles that exist across countries and times.

Distinguishing Segregation and Inequality

Existing techniques. A simple alternative to the profile approach starts from the premise that segregation is not completely conterminous with inequality and that overall segregation consists of invidious and noninvidious components that ought to be identified separately. Semyonov and various collaborators applied this logic to the analysis of cross-national gender segregation and to the analysis of racial segregation across cities in the United States (Semyonov et al. 2000; Semyonov and Jones 1999). Their strategy proceeds by using separate measures of overall segregation and vertical differentiation, and they distinguished between nominal segregation (as measured by ID and the Grusky-Charles

2. Among the advantages of an odds-ratio/log-linear-based approach is that entire rows and columns of a table can be multiplied by varying constants, and the original odds ratios will be preserved. This fact forms the basis for its claim of margin insensitivity (see Watts 1998). A limitation of the odds ratio–based approach is that such ratios can reach their maximum values when segregation is less than "perfect"; for example, in a fourfold table of gender by gender type of job, the odds ratio would reach a maximum value even though some women might be employed in "men's jobs" as long as no men were employed in "women's jobs."

ratio index) and "ordinal occupational differentiation"—inequality (as measured by Lieberson's Index of Net Difference). The rationale for this procedure was explained by Semyonov and Jones (1999:227):

> The summary measures used in past research on gender occupational differentiation can be classified into two distinct and substantively different types: measures of nominal segregation that ignore the ranking of occupations, and measures of ordinal inequality that take the vertical ordering of jobs into account . . . . Although the two are not mutually exclusive—without some degree of segregation there can be no gender inequality—each pertains to and reflects a different theoretical concept.

Understanding that these two dimensions are different is important, and Semyonov and Jones's analysis revealed that the dimensions have different causes. What is left unclear in their approach, however, is the nature of the relationship between so-called nominal and ordinal measures. I argue for a more explicit representation of this relationship in which their measures of *nominal* segregation are construed as measures of "overall segregation" (sometimes called "total segregation") that necessarily include differentiation that is both invidious and noninvidious. In other words, a substantial value on the ID (or any measure of "nominal" segregation) is a necessary, *but not sufficient*, condition for a high level of occupational inequality between the sexes. Therefore, approaches that allow for an explicit decomposition of "total" segregation into its components need to be considered.

Along these lines, researchers in Great Britain and Canada have been arguing for at least 20 years for a paradigm that distinguishes vertical and horizontal dimensions of occupational segregation (Blackburn et al. 2001; Blackburn and Jarman 1997; Hakim 1981). Recently, they developed a set of techniques that attempts to capture this dimensionality. Stated differently, their approach asks how much of the overall difference in men's and women's occupational distributions involves inequality between the sexes in occupational outcomes. These researchers departed from the methods discussed in the preceding paragraph by suggesting a measurement technique in which an overall level of segregation can be decomposed into a horizontal and a vertical component. Their technique is based on computing the Somer's D measure of association under two circumstances. To measure overall or maximal segregation, a set of K occupations would be ordered from the most to the least female. Following the normal methods for calculating the Somer's D statistic, the number of "differently ordered" pairs is subtracted from the number of "similarly ordered" pairs, and the result is divided by the total number of pairs that differ on the independent variable (in this case, the product of the number of male and female workers in the marginal of the table). To measure the degree of vertical segregation, Somer's D is calculated a second time, this time with occupations ordered on whatever vertical scale of differentiation seems appropriate—income, skill, and so forth. By implication, horizontal segregation is the difference between the total and vertical components. This is a clear advance over other techniques insofar as the horizontal dimension can now be assessed in its own right. It is limited, however, because occupations can be ordered only by a single dimension at one time. Although it is possible to combine dimensions of inequality in a prior data-reduction step, this manipulation assumes that inequality consists of the commonality of income and, say, occupational status rather than allows for unique invidious contributions from each (see Blackburn et al. 2001). Further discussion of the potential for considering multiple components of inequality is deferred until after I present the results.

Grusky and Pager (1998) proposed an alternate means of identifying inequality-related and horizontal segregation. This second approach uses log-multiplicative contingency-table methodology and has the additional advantages associated with odds ratio–based approaches—most important, implicit standardization for marginal distributions. Grusky and Pager presented a variety of association models that are appropriate for measuring occupational segregation. Of the most interest in the present context is a model that they labeled a Class III model, which has the following form:

$$m_{ij} = \alpha\beta_i\gamma_j e^{(\Phi\tau_i\mu_j) + (\theta\omega_i\eta_j)}. \tag{1}$$

Taking logs, one obtains:

$$\log m_{ij} = \lambda + \lambda_i^K + \lambda_j^S + (\Phi\tau_i\mu_j + \theta\omega_i\eta_j), \tag{2}$$

where λ_i^K is the marginal effect for membership in the *K*th occupation; λ_j^S is the marginal effect for membership in the *S*th gender; μ_j is the estimated gender score in the first-association dimension; η_j is the estimated gender score in the second-association dimension; τ_i is the a priori occupation score in the first-association dimension; and ω_i is the estimated occupation score in the second-association dimension. This equation represents a log-multiplicative model with two dimensions of association (which are specified in parentheses).[3] The τ parameters are a set of fixed row (occupation) scores that can represent income values, prestige scores, or any other inequality-related measure. These parameters are defined a priori and are not estimated by the model. The μ parameters represent gender in the first dimension of association, and while their values are not specified a priori*,* they are determined by the constraint that all sets of association parameters have a mean of 0 and a standard deviation of 1. Thus, the first dimension captures the association between the a priori occupational inequality (e.g., income) scores and gender, and, therefore, it measures the vertical component of segregation. The second term in which both occupation and gender scores are estimated by the model is orthogonal to the first dimension, and it captures a residual association that reflects nonvertical or horizontal association.

Most relevant to the current discussion is that each of these two components contains a coefficient that represents the degree of intrinsic association for that dimension. Thus, the Φ coefficient is a parameter that captures the extent to which the exogenously determined, hierarchical row scores are associated with gender. The θ coefficient represents a similar quantity for the association between gender and the residual row scores that are, in fact, estimated from the data. These coefficients, which are not present in a simple log-linear model, are directly involved in the formulas for the estimated log odds ratios and can be compared to provide a measure of the relative sizes of "vertical" and "horizontal" segregation.[4] Because these parameters are directly related to the log odds

3. The log-multiplicative model presented by Grusky and Pager (1998) is an application of the more general method of association models introduced by Goodman (1987) and Clogg (1982). The model in the text belongs to the more general class of RC(M) models described by Becker and Clogg (1989). What differentiates these models is the ability to specify multiple dimensions of association (as represented by the Φ and θ coefficients).

4. For example, in the case of the Φ coefficient, the component of the log odds ratio attributable to vertical segregation is calculated as Φ times the difference of the adjacent row scores times the difference of the adjacent column scores. Assume in a hypothetical table that column 1 contains males, column 2 contains females, that the income score of row 1 is 1.5 and the income score of row 2 is 1.0. If the Φ coefficient were 1.0, it would mean that the log odds in favor of a female being in a high-income occupation would be decreased by 1.0 or $1.0 \times [1.0 - .5] \times [1.0 - (-1.0)]$.

The estimates of all log-multiplicative model parameters were obtained from the LEM program (Vermunt 2003), which includes documentation and executable modules for this program that can be downloaded. The scaling option used to estimated row and column scores in these models is labeled "uniform" weights and produces scores that have a sum of 0 and a standard deviation of 1. Because of this choice of scaling, the association parameters for the two different dimensions can be readily compared because they are on the same scale.

Some log-multiplicative RC(M) models can also be estimated with Eliason's (2003) Categorical Data Analysis System. A disadvantage of this software is that it provides less flexibility in specifying model constraints than does the LEM program.

ratios, they produce measures of association that are insensitive to the marginal distribution of the tables.

A new approach. I now turn to a set of proposed measures that contain similarities to both the previous methods. That is, log-linear (but not log-multiplicative) methods are used to characterize both the overall dependence of occupation on gender and the amount of that dependence that is associated with various hierarchical features of the occupations, such as their earnings, prestige, and so forth. And as in Blackburn et al.'s approach, an overall measure of segregation is decomposed algebraically into components. The primary vehicle for accomplishing this goal is a procedure for norming the log-likelihood ratio chi-square statistic that is routinely obtained when one fits any log-linear model. This normalization is relatively simple to compute in the case of occupational gender segregation (or other $N \times 2$ tables), and it produces results that are consistent with those from the more limited earlier techniques.

Working from the premise that the basic occupational segregation table is essentially a $K \times 2$ contingency table, one can construe the problem of measuring segregation in such a table as a special case of measuring association in general. In the literature on measuring association in contingency tables, there are several different approaches. The more familiar of these strategies are various techniques using the logic of proportional reduction of error, analogies to the correlation coefficient, and attempts to normalize the Pearson chi-square statistic[5] (see Bishop, Fienberg, and Holland 1975:376–93; Reynolds 1977:46–58). The approach that I take is the latter—a normalization of a chi-square statistic. However, the statistic that I normalize is the likelihood-ratio chi-square statistic. Thus, it can also be shown that under certain sets of conditions, the likelihood-ratio chi-square statistic for the model of row by column independence achieves a maximum value in "observed" tables that are characterized by "perfect" association. The definition of the log-likelihood ratio statistic, or G^2, used here is

$$G^2 = 2\sum f_i \cdot \log \frac{f_i}{m_i}, \tag{3}$$

where the values of m_i are frequencies expected under the model of row and column independence, and the values of f_i are observed frequencies. For example in a $K \times 2$ table (K representing the number of occupational categories, 2 representing the number of sexes) in which both marginal distributions have equal cell frequencies, the maximum value that G^2 for the independence model can reach is $2 \cdot n \cdot \log 2$.[6] (See Appendix A for the derivation.)

In a more general case—that is, where the basic segregation table has unequal marginals—the maximum value of G^2 can also be calculated under the assumption that each occupation consists exclusively of males or exclusively of females. (However, it is possible that there are some empirical distributions in which it is impossible to reproduce the gender marginal distribution if each row, i.e., occupation, is required to have one zero and one nonzero cell. See Appendix B for a fuller discussion of this matter.) With perfect association between gender and occupation, the maximum G^2, is equal to

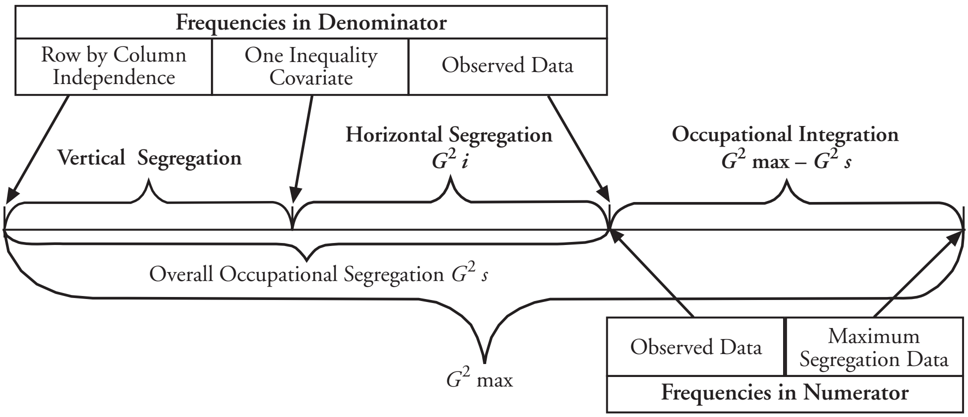
$$2n\left\{p_m \log\left(p_m\right)^{-1} + \left[\left(1-p_m\right)\log\left(1-p_m\right)^{-1}\right]\right\}. \tag{4}$$

To create a measure of occupational gender segregation, one expresses the G^2 value (the one obtained from the model of row and column independence applied to the basic

5. Under certain conditions, the correlation-based measures of association are interpretable as normalized chi-square statistics (Bishop et al. 1975:386).

6. This is true if there are an even number of occupational categories. In a $K \times 2$ table, where K is odd, the maximum obtainable value is $2 \cdot (n - (n / k)) \cdot \log 2$.

Figure 1. Measuring Segregation With Inequality Covariates



segregation table) as a ratio to the maximum possible value (i.e., overall segregation = G^2 Independence / G^2 Maximum). When gender and occupation are statistically independent, the calculated G^2 value for the independence model and for the ratio is 0 (see Figure 1).[7] In contrast, in cases of extreme segregation, the calculated value of G^2 for the independence model is high, and the ratio tends toward 1. The unique advantage of this approach is revealed, however, when one recognizes that the dependence of occupation on gender, which is indexed by the G^2 statistic associated with the independence model, can itself be "explained" by adding other variables to the model.

For example, occupations can be characterized by one or more vectors of inequality-related characteristics, such as income, prestige, working conditions, and skill. As an illustration, assume that the median annual earnings in each of K occupations is τ_i. Then, the basic model of row and column independence can be modified as follows:

$$\log m_{ij} = \lambda + \lambda_i^K + \lambda_j^S + \beta\tau_i, \tag{5}$$

where K refers to the occupational categories found in the rows of the table and S refers to the sex categories found in the columns. This model is a special case of the so-called column-effects model, in which each column of the table is characterized by a unique coefficient of interaction for the scores associated (τ_i) with the rows.[8] After this model is estimated, a new G^2 value, which can be symbolized as G_I^2, is obtained that can be compared to both the maximum possible G^2 value as was just described, or to the G^2 value obtained from the model of row and column independence, which is symbolized as G_S^2. Substantively, the ratio of G_I^2 to G_S^2 represents the proportion of overall segregation that, in this example, is unconnected to inequality in earnings, a measure corresponding to

7. As Figure 1 also shows, the maximum G^2 value (which measures *potential* occupational segregation for any table) can be decomposed into two arithmetic components: observed occupational segregation and occupational integration (i.e., potential segregation that does not materialize).

8. Technically, the column-effects model is written as $\log m_{ij} = \mu + \lambda_i^K + \lambda_j^S \mu_j \tau_i$, where the μ_j refer to $j - 1$ column effects estimated from the data. In the representation in the text, the μ_j term is replaced by a single coefficient because there are only two columns and one effect (see Agresti 1990:269–71; Feinberg 1980:62–67).

Blackburn and Jarman's (1997) concept of horizontal segregation. By analogy, the complement of this ratio, or $(G_S^2 - G_I^2)/G_S^2$, can be taken as a measure of the proportion of total segregation that is invidious or as a measure of the extent of vertical segregation.

In technical terms, this approach differs from the Grusky-Pager (1998) approach in one fundamental way. Both methods contain model terms for vertical dimensions of segregation: $\beta\tau_i$ in the case of the log-linear model approach; $\Phi\tau_i\mu_j$ in the Grusky-Pager log-multiplicative approach, but the measure of segregation is different. The new method measures segregation as "strength of association" by norming a measure of model fit, not by referencing basic parameters of the log-linear model.

Comparison. To compare these three approaches (see Table 1), I begin by considering the types of variables that can be used to represent the vertical inequality dimension. One characteristic shared by the normed G^2 and the log-multiplicative approach, but not by the Somer's D approach, is that the two former techniques allow each occupation to be characterized by the actual scalar value that attaches to each occupation. For example, in the case of income as an index of inequality, each occupation could be characterized by the amount that its average incumbent earns—that is, so many marks, dollars, pesos, or kroners—and does not simply use the income rank of the occupation category as the measure of inequality. Of course, these methods could be easily modified by substituting income ranks for scalar value (i.e., ordinal for cardinal numbers), but the use of scalar values seems more reflective of a concern for inequality of outcome than does the use of ranks. The same principle follows without alteration for any other dimension of inequality that may be considered.

In another regard, however, the G^2 and the Somer's D approaches have one feature that sets them apart from the log-multiplicative parameter approach. In both of the former, but not the latter, there is a measure of "total" segregation that can be decomposed into a vertical and a horizontal component. With the log-multiplicative approach, this is not the case. In that schema, one obtains a measure of vertical segregation and of horizontal segregation, but the two, when added together, do not produce a measure of overall segregation that is obtainable by any other means. What one is left with is choosing between (1) approaches that measure overall segregation and vertical segregation and derive horizontal segregation as a "residual" and (2) an approach that measures vertical segregation as a parameter and all other associations as a parameter, labeling the latter as horizontal segregation. Of course, in the second approach, the association parameter for horizontal segregation will change as more vertical or inequality factors are added to the model. Although one can make assertions about the relative size of vertical and horizontal segregation tendencies in each case, the G^2 and Somer's D approaches also allow statements about the proportion of overall segregation that is associated with inequality.

Another consideration in differentiating these approaches is the extent to which each is "margin free," or the extent to which the results vary when occupational and/or gender distributions are standardized. The G^2 measures and the Somer's D approach are sensitive to the marginal totals of the table, as are most known measures of association for $I \times J$ tables (see Bishop et al. 1975:392). A further modification of these approaches is possible that would achieve the goal of marginal insensitivity. If one accepts the basic dictum of log-linear models that odds ratios define the nature of association in contingency tables, the method of iterative proportional fitting (IPF) can be used to construct a new table with the necessary characteristics. That is, the transformed table will preserve all of the odds ratios present in the unstandardized table, and its marginal distributions will have equal frequencies throughout. In any set of segregation tables, comparisons made across the standardized tables (i.e., those with equal marginals) will be insensitive to varying occupational or gender distributions present in the original tables. Following this transformation, the procedures outlined above for the G^2 approach can be applied in

Table 1. Comparison of Methodologies for Separating Segregation and Inequality

	Cardinal Inequality Values?	Allows Decomposition of Overall Segregation?	Margin-Free?	Multiple Inequality Dimensions?[a]
Log-Multiplicative Association Parameter (Grusky and Pager 1998)	Yes	No	Yes	Yes[b]
Somer's *D* (Blackburn and Jarman 2001)	No	Yes	No	No[c]
Normed G^2	Yes	Yes	Yes[d]	Yes[e]

[a]See the Discussion section for more information.

[b]Assuming identification restrictions.

[c]Only with a prior data-reduction step.

[d]After table standardization.

[e]Provided that the dimensions are consistently ordered by gender type of job.

their entirety, recognizing that the maximum-association formulas are now those that are defined for tables with equal marginal frequencies.

APPLICATION

It is well known that the level of gender segregation varies across societies. Although the methods described here can be applied either within societies, where cities, industries, or other units provide cases for analysis, or between societies, the question of horizontal versus vertical occupational segregation by gender seems especially compelling when one makes comparisons across units like societies that have distinct histories and legal structures.

In recent years, the International Social Survey Program (ISSP) has gathered roughly comparable data from samples of European, English-speaking, and other societies. I amalgamated data from two consecutive ISSP surveys: the ISSP Role of Government III (1996) and the ISSP Work Orientations II (1997). Merging adjacent years enhanced sample sizes for countries that were included in both waves of data, and additional cases were obtained for societies that were covered in only a single survey. Also, because I analyzed only basic background information on occupation, gender, earnings, and hours worked, it was of no consequence that the special topic varied across these surveys. In some instances, the lack of comparable occupational coding ruled out the use of data from countries that otherwise would have been included.[9]

The occupation classification I used is a recoding of the 1988 International Standard Occupational Classification into 19 categories.[10] Clearly, more occupational categories

9. Countries that were excluded on this basis were Great Britain, Northern Ireland, Italy, the Netherlands, Japan, Spain, and Bangladesh. In addition, some countries were excluded for one of the two survey years because of various limitations. Countries that were included only in 1996 were Australia, Ireland, and Latvia, which were not surveyed in 1997; countries that were included only in 1997 (because there was no occupational comparability across years) were the United States, Norway, Sweden, and Israel; countries that contributed data for both years were Germany, Hungary, the Czech Republic, Slovakia, Poland, Bulgaria, Russia, New Zealand, Canada, the Philippines, France, Cyprus, Portugal, Denmark, and Switzerland.

10. The following is a list of occupational categories that were used in the analysis in which each group was followed by the 1988 ISCO three- and four-digit codes that constitute each category: managers, 110–131 (1000–1320); professionals, excluding teachers, 200–223 (2000–2236); teachers and professors, 231–235 (2300–2359); other professionals, 240–250 (2400–2519); technicians, 311–324 (3000–3242); associate professionals (teaching), 331–334 (3300–3342); other associate professionals, 341–348 (3400–3492); clerks, 410,

would have been useful, but the relatively small sample sizes within some countries made it impossible to use them. This classification system represents a compromise based on that fact.

Two measures of occupational inequality were used in the analysis. The primary one was yearly earnings in the occupation, which was measured as the proportion of respondents in the occupation who reported earnings above the country's median earnings (across all occupations). For example, in Hungary, 45% of the secretaries had earnings above the median level (approximately 18,500 *forints* in the ISSP sample); for managers in Hungary, the comparable value was 79%, and for laborers, it was 29%). In addition, in some of the analyses, this earnings measure is represented by two separate variables: one for the white-collar sector and one for the blue-collar sector. Essentially, the upshot of using two variables is that the relation between income and "femaleness" is allowed to vary by sector. This specification was used because preliminary analyses suggested that income segregation between male and female workers was larger in lower-status, manual occupations than it was toward the top of the occupational hierarchy.

RESULTS

Univariate Patterns

I begin by considering how values on the proposed new indices compare to existing segregation measures. Country-by-country results are presented for the margin-sensitive, "unstandardized" indices in Figure 2 and for indices that are either occupationally standardized or implicitly margin-free in Figure 3. In addition, correlations among all these indices and the percentage female in each country's nonagricultural labor force are shown in Table 2.[11]

In these results, I included separately values for the G^2 measures, as defined earlier, and for the square root of these measures. Those who are familiar with various measures of association in contingency tables will recognize the latter as an analogue to the Cramer's *V* statistic—a measure that is calculated by taking the square root of the ratio of the Pearson chi-square statistic to its (alleged) maximal value. In measuring gender segregation, this change of scale is most useful in basic descriptive work because it simplifies comparisons of the G^2 measure to the other indices. It was not used for the inequality decomposition discussed in the next section.

The overriding impression made by Figure 2 is that there is high correspondence among the unstandardized measures. The correlations in Table 2 confirm this high correspondence and indicate a somewhat stronger relationship between the ID and Blackburn and Jarman's (1997) Somer's *D* statistic than between the ID and the G^2 measure. (Both of the former, for example, show slightly larger values for Switzerland and slightly depressed values for Portugual than does the G^2 measure.) On balance, however, the newly proposed measure appears to capture the same aspect of underlying reality as do the existing measures.

This harmony yields to greater dissonance in the patterns among the standardized measures presented in Figure 3. (In Figure 3, the scale for Grusky and Charles's (1998) A index is presented on the secondary vertical axis at the right side.) Of the four measures

412–450 (4100, 4120–4500); secretaries, 411 (4111–4115); personal services, 510–515 (5100–5152); protective services, 516 (5160–5169); salespersons, 520–523 (5200–5230); agricultural occupations, 610–621 (6100–6219); construction crafts, 700–714 (7000–7144); other crafts, 720–791 (7200–7900); plant and machine operators and assemblers, 810–831, 833–834 (8100–8290,8330–8340); drivers, 832 (8320–8324); laborers, 910–912, 914–933 (9100–9120,9140–9333); and domestic workers, 913 (9130–9133).

11. All measures (except for the parameters of the log-multiplicative RC(M) models) were calculated by means of an SAS Macro program, which was written by the author and will be made available to interested users on request.

Table 2. Correlations of Measures of Segregation

	Unstandardized				Standardized					
Measure	G^2 Based	Sq. Rt. G^2 Based	ID	Somer's *D*	Stzd. G^2 Based	Sq. Rt. Stzd. G^2 Based	Marginal Matching	A Index	Stzd. ID	Percentage Female
Unstandardized										
G^2 based	1.000	.995	.972	.985	.656	.670	.964	.356	.785	.040
Sq. rt. G^2 based	.995	1.000	.971	.990	.657	.676	.958	.369	.780	.025
ID	.972	.971	1.000	.981	.546	.564	.991	.550	.739	–.038
Somer's D	.985	.990	.981	1.000	.596	.615	.975	.268	.748	.017
Standardized										
Stzd. G^2 based	.656	.657	.546	.596	1.000	.998	.536	.704	.912	.153
Sq. rt. stzd. G^2 based	.670	.676	.564	.615	.998	1.000	.552	.710	.915	.144
Marginal matching	.964	.958	.991	.975	.536	.552	1.000	.201	.734	–.025
A index	.356	.369	.268	.265	.704	.710	.201	1.000	.554	–.143
Stzd. ID	.785	.780	.739	.748	.912	.915	.734	.554	1.000	.196
Percentage Female	.040	.025	–.038	.017	.153	.144	–.025	–.143	.196	1.000

displayed, the marginal-matching index is clearly the least consistent with the other measures. (For a critique of marginal matching, see Watts 1994.) Table 2 reveals that its correlation with the other measures is invariably lower than their mutual intercorrelation. In fact, it appears to be more strongly related to the unstandardized measures than to the standardized ones. Among the remaining measures, the strongest correspondence is between the G^2 measures and the size-standardized Index of Dissimilarity (SSID); the weakest is between the A index and the SSID. However, the G^2 measure has some resemblance to the A index insofar as their correlations with percentage female are smaller than the correlation between the SSID and percentage female. Again, the patterns here confirm that the choice among these three measures may produce little substantive difference in any theoretically motivated analysis of segregation patterns.

Vertical Segregation

The central issue, however, is how these measures compare in their calibration of a vertical component of occupational gender segregation. In this endeavor, I am limited to the three segregation-measurement approaches described in Table 1: one based on Somer's *D*, the G^2 approach developed here, and Grusky and Pager's (1998) log-multiplicative parameter approach. The decomposition of Somer's *D* is summarized in the first three columns of Table 3.[12] (The amount of horizontal segregation can be easily derived by subtracting the values in the second column from the values in the first.) The values shown in the third

12. Recall that this statistic is computed as the surplus of "similarly ordered" over "differently ordered" pairs of cases, divided by the total number of pairs of cases that differ on the independent variable (in this case, gender). In the Blackburn and Jarman (1997) approach, overall segregation is defined as the Somer's *D* that results when occupations are ordered by percentage female. Vertical segregation is defined as the same statistic that results when the occupations are sorted by whatever inequality scale is being used.

Figure 2. Comparison of Unstandardized Segregation Measures: Nonagricultural Occupations

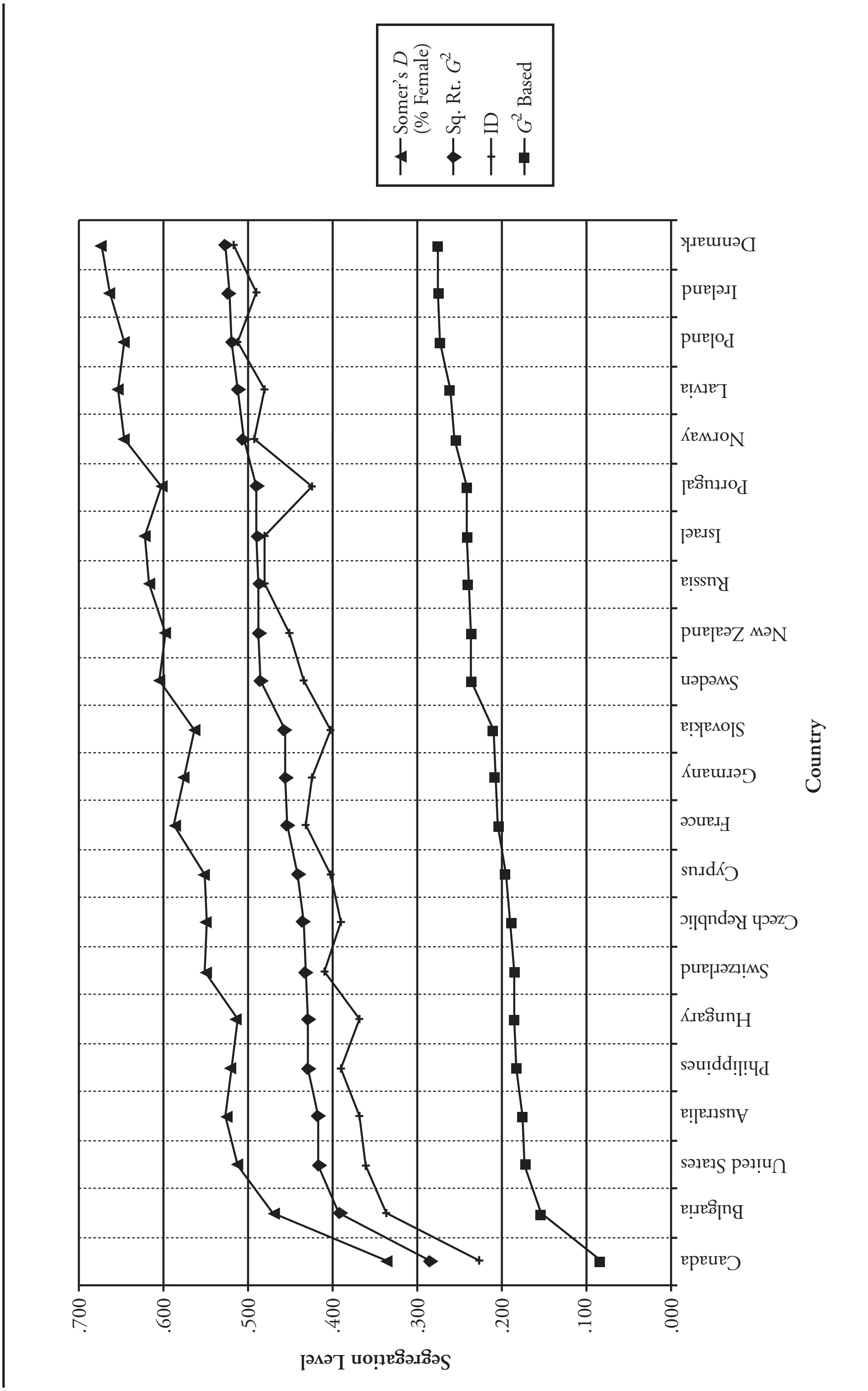


Figure 3. Comparison of Standardized Segregation Measures: Nonagricultural Occupations

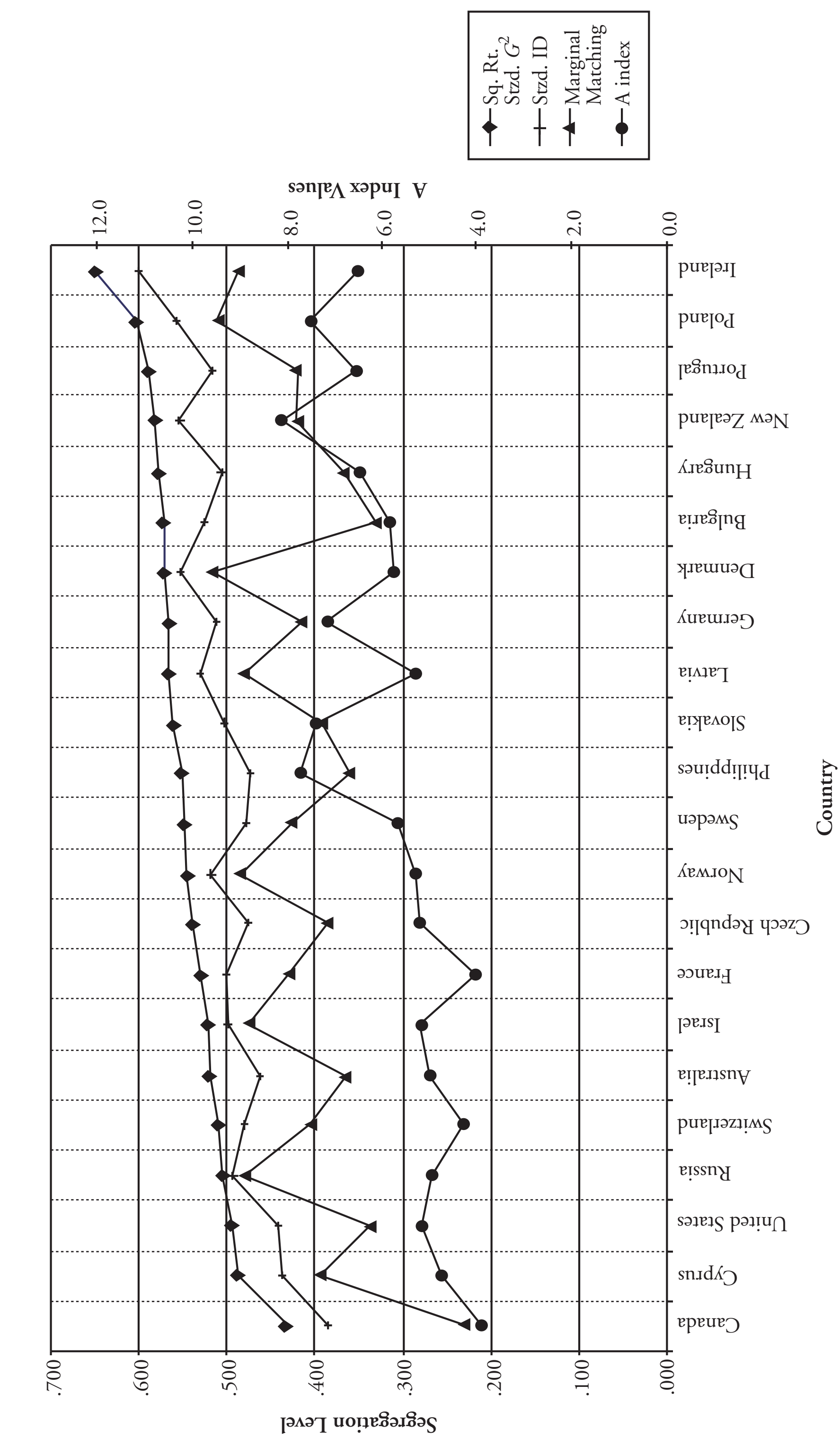


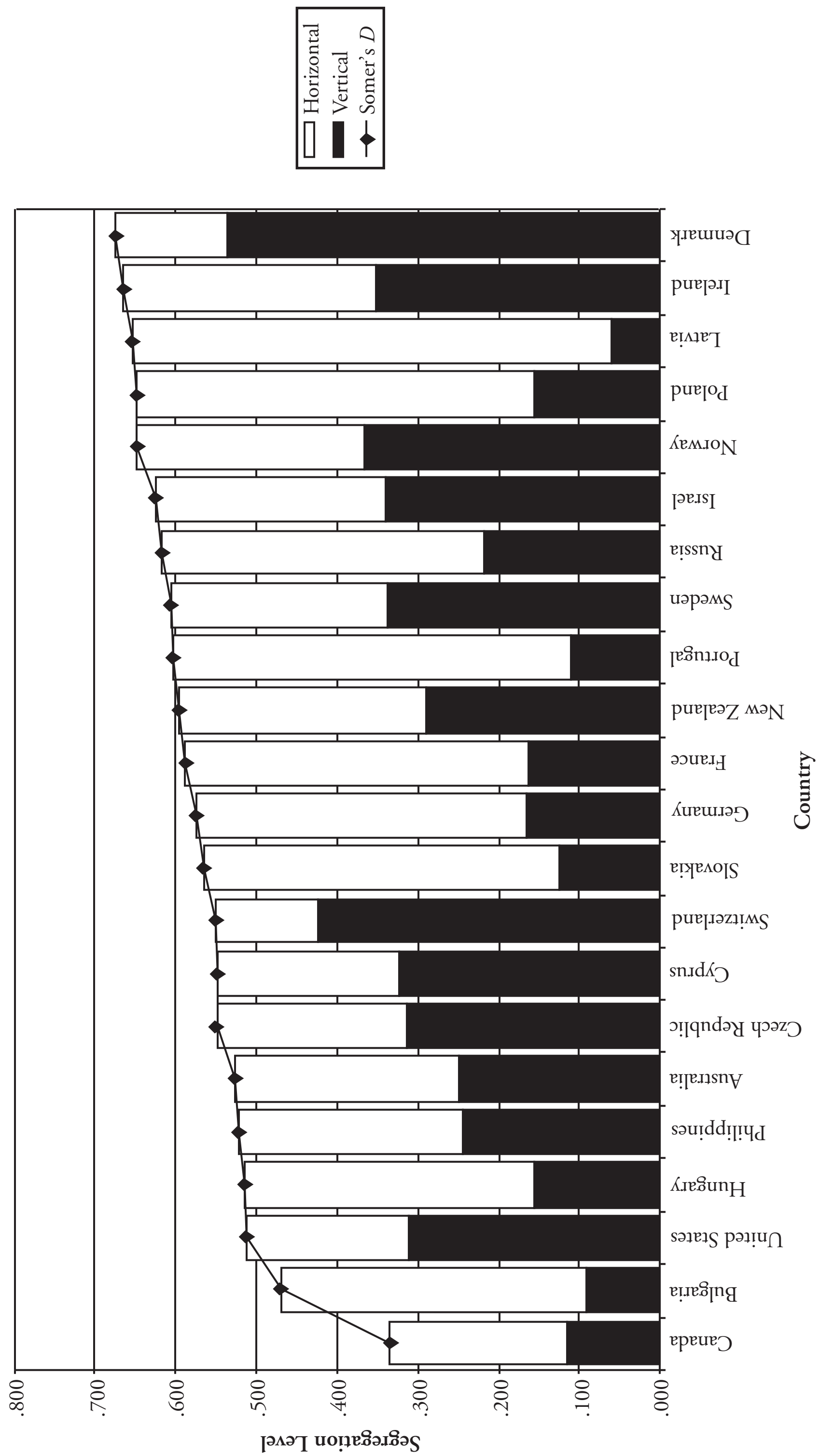
Table 3. Measures of Total and Vertical Segregation

	Somer's *D* Based			G^2 Based			Log-Multiplicative Income Model		
Country	Overall	Vertical	Proportion	Overall	Vertical	Proportion	Overall	Phi, Inc. (Vertical)	Implied Proportion
Canada	.335	.116	.347	.185	.081	.436	—	.312	.207
Bulgaria	.470	.091	.194	.326	.099	.305	—	.081	.045
United States	.513	.310	.604	.243	.157	.646	—	.567	.326
Hungary	.514	.157	.305	.333	.230	.690	—	.354	.240
Philippines	.521	.246	.473	.303	.160	.527	—	.407	.174
Australia	.526	.249	.474	.268	.152	.567	—	.564	.323
Czech Republic	.550	.314	.572	.290	.236	.813	—	.510	.341
Cyprus	.550	.323	.586	.236	.109	.460	—	.454	.430
Switzerland	.552	.425	.771	.259	.226	.871	—	.686	.623
Slovakia	.565	.124	.220	.315	.181	.574	—	.146	.077
Germany	.575	.166	.289	.320	.251	.786	—	.269	.134
France	.588	.163	.277	.279	.208	.745	—	.363	.236
New Zealand	.596	.290	.486	.338	.243	.718	—	.881	.327
Portugal	.603	.110	.182	.347	.057	.163	—	.415	.207
Sweden	.606	.336	.555	.300	.230	.766	—	.484	.298
Russia	.618	.220	.356	.254	.174	.684	—	.383	.340
Israel	.624	.341	.547	.271	.162	.600	—	.438	.262
Norway	.647	.366	.565	.297	.249	.839	—	.428	.353
Poland	.648	.156	.241	.362	.296	.816	—	.759	.324
Latvia	.655	.062	.095	.319	.184	.575	—	.065	.048
Ireland	.665	.351	.528	.420	.152	.363	—	.543	.206
Denmark	.674	.534	.793	.325	.211	.650	—	1.131	.481
Mean	.573	.248	.430	.300	.184	.618	—	.465	.273

column are the proportion of overall segregation that is associated with vertical inequality. In this instance, the amount of vertical segregation was determined by ranking each country's occupational categories by the income measure described in the previous section. A graphic view of these patterns is shown in Figure 4.

On average, vertical segregation constitutes slightly less than half of all occupational segregation, reinforcing the conclusions that Blackburn and collaborators (Blackburn et al. 1995, 2001; Blackburn and Jarman 1997) have offered. Moreover, there seems to be only a moderate association between the size of the vertical-inequality component and the overall level of segregation. Latvia, for example, shows a relatively high level of segregation overall, but not much of it is attributable to income differences among the occupations. In contrast, Switzerland has tendencies in the opposite direction—slightly

Figure 4. Components of Overall Segregation: Somer's *D* Approach



below the average overall segregation, but a fairly large vertical component. The Pearson correlation coefficient between these measures is about .36.

The next three columns of this table present similar decompositions for the standardized G^2 measure of segregation. In the first set of columns, results are shown when the income covariates are added to the log-linear association model.[13] Figure 5 contains the parallel chart of these outcomes. Compared with the Somer's D results, these results indicate some interesting differences from those in the first panel. First, the vertical component now amounts to about 60% of the overall segregation in the average country. There are also some different results for specific countries. For example, Poland still has substantially high overall levels of segregation, but the new measure indicates that it has a relatively high level of vertical segregation. This apparent increase in the vertical component of occupational segregation in Poland probably reflects the fact that the G^2 measures shown here are based on standardized tables—Poland and some other Eastern European countries may have occupational distributions that are prone to less gender inequality, but once this factor is taken into account, the amount of vertical inequality increases.

A somewhat parallel approach can be followed by fitting the two-dimensional, log-multiplicative model described earlier. Unlike the previous two approaches, this approach does not technically produce a decomposition of an overall segregation index. However, it does allow one to compare the relative magnitude of vertical- and horizontal-association components. A similar graphical display of these estimated "components" is shown in Figure 6, and relevant statistics are presented in the last three columns of Table 3.

The results for this approach are different from either of the previous two. One would expect that this approach would have similarities to each, but for different reasons. Like the Somer's D decomposition, this approach is based on the analysis of a regression-like parameter, rather than a measure of association or model fit.[14] However, like the results for the log-linear decomposition, these association parameters are not sensitive to the marginal distribution of the respective tables and are, in that sense, standardized. Nevertheless, some of the same patterns prevail in this figure. For example, Denmark and Switzerland continue to have relatively high levels of vertical segregation, and Bulgaria, Portugal, Ireland, and Slovakia are relatively strong on horizontal segregation.

Predictive Patterns

Having established that these new measures provide useful descriptive information, I now offer a preliminary assessment of their analytic utility. That is, can they be used to provide meaningful insights if they are used as dependent variables in standard predictive models? Of course, only 22 cases are available for analysis here, and that number constrains both the number of predictors and the statistical power of the models. With this caveat in mind, I present in Table 4 some regression models with a small number of independent variables. Previous research has shown the importance of level of economic development, which is represented here by the gross national product (GNP).[15] In addition, these studies have documented the role of differences in male-female educational enrollment in contributing to occupational inequality between the sexes (Semyonov et al. 2000). Therefore, the following models include a female-to-male enrollment ratio as reported by the United

13. The coefficient for the income-gender relationship is statistically significant at the .05 level in each country. In almost each instance, the income-gender relationship was stronger among blue-collar occupations than among white-collar ones.

14. In a 2 × 2 table, Somer's D is computationally identical to the difference in the percentage distributions; that is, it is an effect-like parameter.

15. GNP data were taken from the World Bank World Development Indicator database. The actual measure used was the arithmetic mean of GNP per capita (Atlas method) in current U.S. dollars averaged over 1995, 1996, and 1997 (some countries had missing data for one or two years).

Figure 5. Components of Overall Segregation: Standardized G^2 Approach

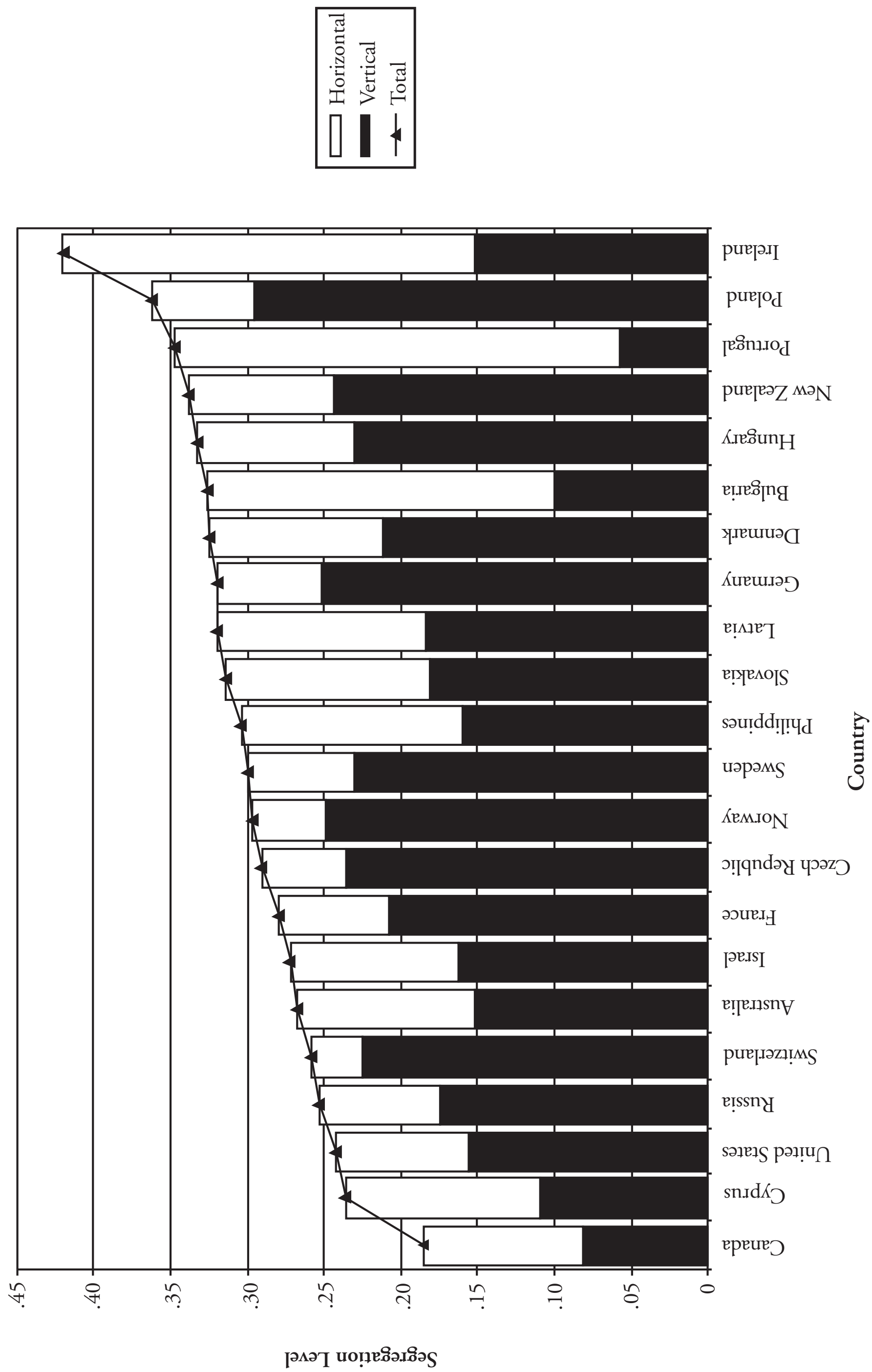


Figure 6. Vertical and Horizontal Segregation as Measured by a Two-Dimensional Log-Multiplicative Model

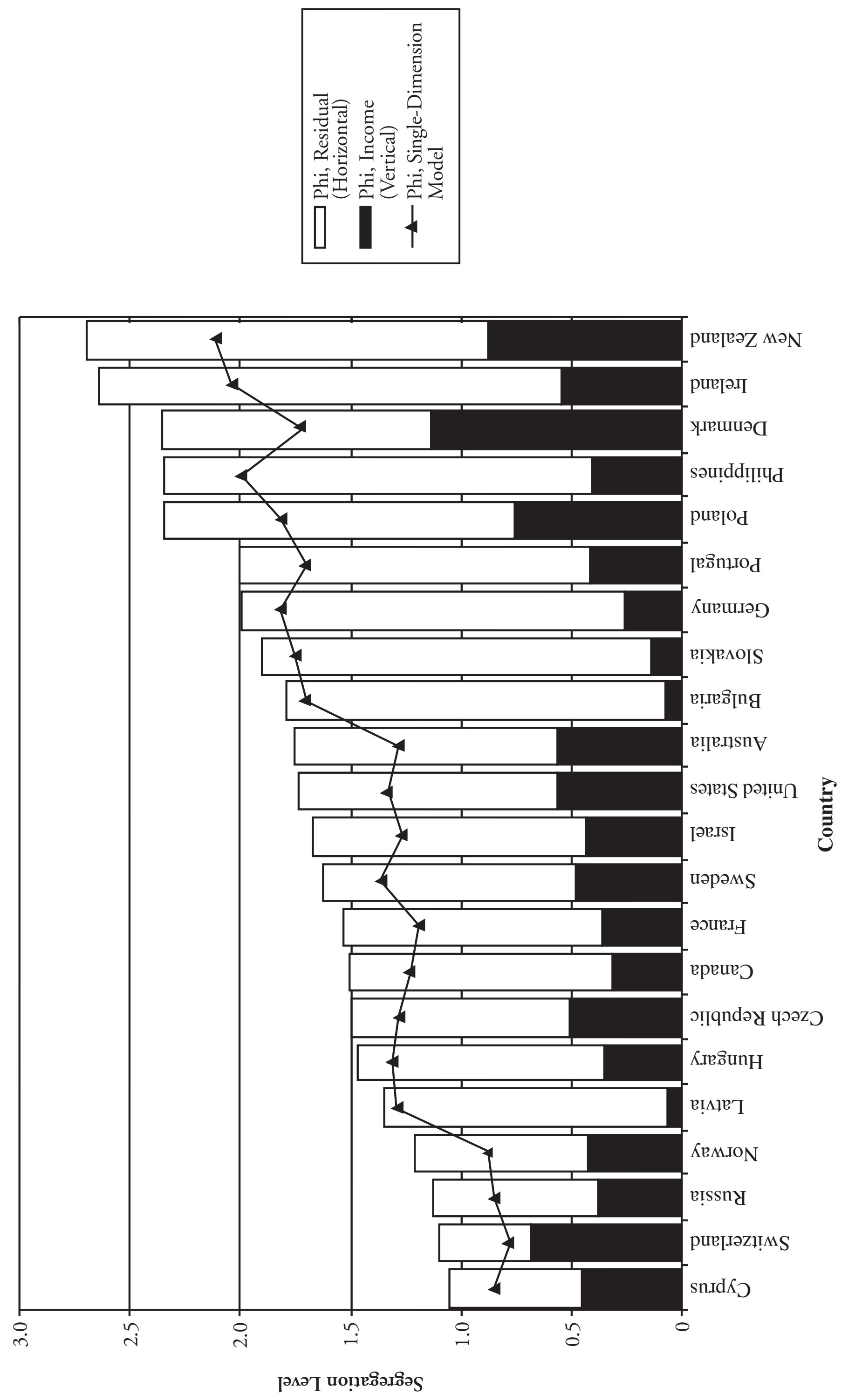


Table 4. Models Predicting Overall, Horizontal, and Vertical Components of Segregation

	Overall Segregation			Horizontal			Vertical		
	b	*t* Value	Pr > |*t*|	*b*	*t* Value	Pr > |*t*|	*b*	*t* Value	Pr > |*t*|
I. Somer's *D* Method									
Intercept	0.926	3.711	.002	0.335	1.199	.249	0.592	2.451	.027
GNP (000s)	–0.001	–0.463	.650	–0.009*	–3.125	.007	0.008*	3.135	.007
Female enrollment ratio	–0.004	–1.587	.133	0.001	0.442	.665	–0.005*	–2.152	.048
Scandinavia	0.099	1.556	.141	0.076	1.072	.301	0.023	0.370	.717
Europe	0.014	0.234	.818	0.173*	2.597	.020	–0.159*	–2.761	.015
Former socialist	–0.062	–0.713	.487	0.019	0.199	.845	–0.082	–0.968	.348
Other	–0.035	–0.480	.638	–0.081	–0.983	.341	0.046	0.640	.532
II. Standardized G^2 Method[a]									
Intercept	0.650	4.348	.001	0.400	2.070	.056	0.250	1.305	.212
GNP (000s)	–0.004*	–2.273	.038	–0.007*	–3.306	.005	0.003	1.556	.140
Female enrollment ratio	–0.003†	–2.027	.061	–0.001	–0.706	.491	–0.002	–0.869	.398
Scandinavia	0.034	0.885	.390	0.007	0.151	.882	0.026	0.538	.598
Europe	–0.001	–0.036	.972	0.010	0.215	.832	–0.011	–0.245	.810
Former socialist	–0.106†	–2.023	.061	–0.165*	–2.452	.027	0.060	0.891	.387
Other	–0.105*	–2.372	.032	–0.100	–1.745	.101	–0.005	–0.092	.928
III. Log-Multiplicative Model Paramaters[a]									
Intercept	—	—	—	2.594	1.995	.064	0.981	1.221	.241
GNP (000s)	—	—	—	–0.042*	–3.016	.009	0.007	0.796	.438
Female enrollment ratio	—	—	—	–0.003	–0.211	.836	–0.006	–0.718	.484
Scandinavia	—	—	—	–0.009	–0.028	.978	–0.009	–0.044	.965
Europe	—	—	—	–0.030	–0.096	.925	–0.251	–1.307	.211
Former socialist	—	—	—	–0.951*	–2.094	.054	–0.258	–0.919	.373
Other	—	—	—	–0.718†	–1.864	.082	–0.156	–0.657	.521

[a]One inequality dimension (income).

†$p < .10$; *$p < .05$

Nations in 1995.[16] Finally, the models include a set of dummy variables representing the type of society. These models capture the following categories: Scandinavia (Denmark, Sweden, Norway), English speaking (Australia, Canada, Ireland, New Zealand, United States), former Socialist (Bulgaria, Czech Republic, Hungary, Latvia, Poland, Slovakia, Russia), other European (France, Germany, Portugal, Switzerland), and other (Cyprus, Israel, Philippines). In the actual analyses, English speaking is the omitted category.

The first panel of Table 4 presents results using the Somer's *D* methodology. There are two apparent findings of interest. First, level of development, as measured by the GNP, has counterbalancing and offsetting effects on the degree of overall segregation. According to

16. The measure used was the female first-, second-, and third-level combined gross enrollment ratio reported by the United Nations Development Programme (1995:51–52).

this model, more-developed societies have less horizontal segregation but higher vertical segregation. One might suspect that the former is a measure of traditional, but noninvidious, sex roles, while the latter reflects the kind of inequality resulting from the development of an industrial and postindustrial gendered labor force. Societies in which women are relatively overrepresented in school enrollment tend to have less segregation that is associated with inequality. This variable has little effect on horizontal segregation, and its effect on overall segregation is negative but statistically insignificant. Finally, compared with the English-speaking countries, there is a tendency for the other European societies to have slightly more horizontal segregation and less vertical segregation.

In the next panel, the results for parallel models are applied to the standardized G^2 variables. The main difference between these results and those in the first panel is that this method produces lower and, I believe, more realistic estimates of the relative size of the horizontal-segregation component. The effects of the GNP are now muted compared with those just noted. Although the negative relationship of the GNP with the horizontal component is still statistically significant, the positive relationship to the vertical component is not. When these tendencies are combined, the effect of the GNP on overall segregation is slightly negative. The factor of relative female school enrollment exerts a negative effect on overall segregation, but this effect is now made up of two small and, by themselves, insignificant effects on horizontal and vertical segregation. Other European countries are no longer different from the comparison country, but there is an interesting result for the former socialist societies. They are significantly lower on horizontal and overall segregation, but not much different on the vertical dimension.

In the final panel, results for the predictions of the log-multiplicative association parameters are shown. As I previously mentioned, it is no longer possible to combine the effects on vertical and horizontal segregation to come up with an effect on overall segregation. Nevertheless, one sees a lot similarity between these results and those for the standardized G^2 models. The largest discrepency is that in the log-multiplicative approach, there is a negative association of societies in the other category with horizontal segregation.

Taken as a whole, the results in this table point to the consequences of using methods that standardize for occupational distributions and those that do not. Only the unstandardized Somer's D method produces a positive association between the GNP and vertical (i.e., inequality-linked) occupational segregation. In essence, what this finding means is that more-developed, higher-income societies have occupational distributions that are tilted toward those occupations in which "maleness" and high earnings are linked (and/or those in which "femaleness" and low earnings are linked). That is, it is the size of these occupations as a share of the labor force in the richest societies that produces the effect. Within occupations, there is no difference between rich and poor societies in the extent to which occupational segregation is associated with diminished female earnings.

DISCUSSION

Measuring vertical segregation by adding covariates to log-linear or log-multiplicative contingency-table analysis raises the question of whether adding a *single* vector of scores to the model is sufficient to capture all the gender inequality present in an occupational system. There are, however, both theoretical and technical issues that arise when one contemplates the presence of *multiple* covariates.

From the perspective of theory, the crucial requirement is that one specify conceptually the vertical dimension of inequality that is most important in comparing occupational systems. Different covariates and different sets of covariates will be appropriate, depending on how this dimension is specified. For example, if one defines the key aspect of occupational inequality as *access to economic resources*, a different measure or measures would be included than if one is attempting to capture a concept like *general social* *standing*. Once the appropriate concept is specified, it is then apparent that multiple measures of this concept may be appropriate. Again, with reference to access to economic resources, it would be reasonable to include covariates for each occupation's ability to provide full-time work, as well as a covariate for its average wage level. Or if the crucial vertical dimension is social standing, both prestige and average educational measures may be included. But the very concept of vertical differentiation seems to imply that no more than one concept, although one that may be multiply measured, should be brought to bear on any single analysis.[17]

It is clear that the three statistical approaches can be modified to allow for multiple measures of a vertical dimension, but in slightly different ways. In the Somer's *D* approach, which is based on ranking occupations, to use multiple measures, one is required to engage in a prior data-reduction step (e.g., a principal-components analysis or the equivalent). (Blackburn et al. 2001 computed a simple arithmetic sum of scaled earnings and the Cambridge scale, a measure of "general social advantage," p. 517). In contrast, in the G^2 approach, modifying the log-linear equation on which it is based to add additional inequality terms is trivial. But because the vertical index is based on a measure of goodness of fit, one must be certain that all covariates that are included are related to gender composition in the same direction *and* in the predicted direction. That is, like all chi-square-based measures of strength of association, the G^2 measures presented here are insensitive to the direction of association in the underlying attributes. When the "inequality variables"—for this discussion, I assume that they represent access to economic resources—have the same relationship to gender in *all* units (countries), then the signs of the relationships can be safely ignored and a simple strength-of-association measure is interpretable across all units. (In the results presented here this is true in all instances.) On the other hand, this inconvenience is offset by an advantage. In the log-linear approach, the statistical significance of the addition of any new measures can be easily tested in any empirical case.[18]

Matters are only slightly more complicated in adding covariates with the log-multiplicative approach. Because row scores for the residual (horizontal) dimension are parameters that are *estimated* under this approach, restrictions on these scores must be imposed to have enough degrees of freedom to estimate the model. For each dimension of inequality, an additional restriction must be added, and it becomes increasingly difficult to do so as more dimensions are added to the model. However, because the log-multiplicative approach relies on effect parameters, rather than measures of the strength of association, it reveals the direction of association "automatically." In other words, with the association-parameter, log-multiplicative approach, it is possible to detect and to measure directly "negative" vertical inequalities. If this set of techniques were used as a prelude to a subsequent analytic step similar to that shown in Table 4, it would then be possible to conduct these latter analyses separately for different types of vertical inequality. Adapting the log-multiplicative approach in this manner raises the intriguing possibility of explaining which factors are associated with minorities' segregation into inferior positions (on

17. Some theories of occupational differentiation—for example, the theory of compensating differentials in economics—are not well-suited to a horizontal-vertical framework. In fact, by asserting that every material or psychic "negative" in an occupation must be counterbalanced by an opposing material or psychic "positive," this theory essentially argues that all gender-based occupational segregation is essentially horizontal, at a given level of human capital.

18. In supplementary analyses that are not presented here, the decomposition was recalculated with the addition of a second measure of economic sufficiency, a variable representing median hours worked in each occupation in each country. This addition produced only a slight change in outcomes. As expected, variability in both the absolute and relative amounts of vertical differentiation persisted across countries, and, in almost every country, the inequality component was now the largest contributor to overall occupational gender segregation. Vertical differentiation was the lowest in Bulgaria (31% of all segregation), and the highest in Switzerland (89%). Detailed results are available from the author on request.

some dimension), which factors are linked to minorities' segregation into superior positions (on some other dimension), and which set of factors are associated with minorities' segregation into positions that are merely different—true horizontal segregation.[19]

Effect parameter measures and strength-of-association measures can also produce results that are quantitatively different from each other. One of the first things taught to statistical novices is that slope coefficients and coefficients of explained variation do not always order results in the same way, and the same holds true here. A comparison of results across Figures 5 and 6 shows, for example, that vertical segregation for Germany and Switzerland is markedly higher in Figure 5 than it is in Figure 6. A preliminary investigation of basic patterns suggests, but does not prove, that these discrepancies are associated with large differences in income variances between the two countries. The United States, for instance, has substantially less vertical segregation than Germany does in Figure 5 (based on chi-square values), but it has a larger "effect-parameter" association because of its smaller income variance.[20] Which approach one prefers in this regard is not a matter that is easily resolved on an a priori basis.

CONCLUSIONS

Despite evidence of battle fatigue in the so-called index wars, important refinements are needed in the ways in which social scientists characterize gender segregation and inequality. In this article, I proposed and illustrated sets of measures that remedy shortcomings in existing techniques. One novel solution offered here is consistent with a long-standing tradition in the field of statistics that measures association in contingency tables by normalizing chi-square statistics.

As anticipated, these measures revealed a component of occupational gender segregation that is *not* readily linked to income or other dimensions of inequality. Nevertheless, the different measures explored here produced somewhat different results. When these techniques were applied to cross-national data, only the newly formulated G^2 approach showed that levels of vertical segregation, on average, exceed levels of horizontal segregation. In short, the proposition that *all* occupational gender segregation is directly linked to inequality cannot be supported with existing measures, and there is only tentative evidence that *most* segregation is invidious.

But also, as expected, societies vary markedly in these proportions. Each set of measures showed that in some countries (e.g., Switzerland, Denmark), inequality-related segregation is relatively high and that in other countries (e.g., Canada, Bulgaria), it is relatively low. Furthermore, the results indicate that there is only a modest correlation between the overall level of segregation and the size of the vertical component. Again, this low correlation lends a cautionary note to attempts to reduce gender segregation, at the conceptual level, to gender inequality.

My preliminary analysis of the predictors of overall segregation and its components shed some light on the meaning of these subfactors. In particular, vertical segregation seems to be the weakest in the least-developed countries (as measured by the GNP), indicating perhaps that traditional societies reward male roles in other ways than directly through earned income. Several of the measures also indicated that former socialist countries also have lower-than-expected levels of noninvidious gender segregation.

Although the application in this article was focused entirely on gender segregation in an international context, the method is readily transferable to other units of analysis and can be applied to variability in occupational segregation across cities, industries, regions, and even periods. Moreover, it is also useful for investigating segregation in

19. The G^2 approach would tend to conflate the latter two components.

20. The variance of my income measure across occupations is .053 in Germany and .029 in the United States.

other two-group contexts, such as that between immigrants and native-born workers or between racial groups in societies with “bipolar” racial systems. Like many other measures, it is, of course, sensitive to the level of categorization of occupations or other sets of categories to which it may be applied. For this reason, one may proceed cautiously in applying this technique to geographic segregation across cities or other units.

But to return to the introduction of this article and to some scholars’ uneasiness with the concept of piling index on top of index, should the field proceed in the direction of yet another segregation index (see Grusky and Charles 1998)? What is at stake here is largely a question of social theory. The methods I proposed work relatively well for classification systems with a moderate-to-large number of categories. They are also consistent with the idea that occupations can be meaningfully scaled using one or more exogenously defined indicators of inequality, such as earnings, prestige, and skill. The concept of vertical segregation is most at home in a theory that views labor markets as part of an abstract system of social differentiation.

But when one is focusing on a smaller number of occupational categories and on categories that are intrinsically meaningful in the context being studied, methods that emphasize patterns of occupational concentration, such as the segregation profiles that Grusky and his coauthors derived using log-linear and log-multiplicative techniques, may be preferred. As these researchers suggested, it is the array of underlying institutional forces that gives meaning to the patterns of coefficients produced under this approach. I submit that this embedding of gender segregation in an institutional context weighs against using the profile method, at least initially, in comparative, international analysis. In fact, it is precisely in comparing occupations across highly diverse societies that meaningful and consistent occupational categories are the least likely to be found. On the other hand, close comparative or longitudinal analysis of the occupational division of labor of a single, multiunit firm may be especially fertile ground for the segregation profiles generated by log-multiplicative techniques. Or, for another example, the division of labor constructed around a professional system, such as that associated with American medicine, may be well-suited to this endeavor. In fact, specific institutional developments like changing certification or licensure requirements for nurse practitioners, clinical pharmacists, and physicians’ assistants could be tracked onto the sexual division of labor across times and places. In sum, there is no substitute for a measurement strategy in which the measurement of segregation is chosen according to the theory of segregation (and inequality).

APPENDIX A

The maximum value of G^2 in a $K \times 2$ table with equal marginal frequencies is calculated as follows:

Consider first the case where K is an even number. The number of cases in each row total is therefore equal to n / K, where n is the total number of cases. Under the independence model, each cell frequency is equal to $n / 2K$, and each row of the table contributes an amount to G^2 equal to

$$2 \cdot \frac{n}{K} \cdot \log\left(\frac{n/K}{n/2K}\right) = 2 \cdot \frac{n}{K} \cdot \log 2 \qquad \text{(A1)}$$

because one cell in each of the rows of the maximum-segregation tables is equal to n / K, and one cell is equal to 0. Summing over all rows, the value of $2 \cdot n \cdot \log 2$ is obtained.

Matters become more complex when tables have an odd number of rows because in this instance, equal sex-marginal frequencies cannot be maintained by assigning a 0 cell to each row. In these situations, there are two options: (1) in a single row, assign the cases in that row on a 50–50 basis to preserve equal column (sex) frequencies; doing so has the perverse effect that, for tables with a finite number of rows, tables with odd numbers of rows will have smaller maximum G^2 values than will tables with an even number of rows (see footnote 6); or (2) relax the assumption of equal column frequencies in the table-standardization process. The results appearing in the empirical section opt for the latter solution. In other words, for tables with odd numbers of rows, $(K-1)/2$ rows are assumed to be all male, and $(K+1)/2$ rows are assumed to be all female (or vice versa). Therefore, observed tables are standardized via IPF to have equal row marginals and column marginals of

$$\frac{n(K-1)}{2K} \text{ and } \frac{n(K+1)}{2K}. \tag{A2}$$

Applying the more general results given in Appendix B, the maximum G^2 value for these tables is given by

$$2 \cdot n \cdot \left[\frac{K-1}{2K} \log\left(\frac{2K}{K-1}\right) + \frac{K+1}{2K} \log\left(\frac{2K}{K+1}\right) \right]. \tag{A3}$$

APPENDIX B

The maximum value of G^2 can be calculated for the more general $K \times 2$ case under the assumption that the marginal distributions are such that in each row (occupation) in the table, cases can be assigned to either one sex or the other so that each row contains one cell with observations equal to k_i, the row total, and the other cell contains a 0. Following the basic derivation, I consider the case in which this assumption is not met. I further stipulate that the total number of cases in the table is N, the number of males is m, and the number of females is $N - m$. I begin by assuming that the table is grouped in such a way that the first L rows of the table contain observations (occupations) that, under the model of perfect association, contain only males, and the remaining K–L rows contain observations that, under perfect association (that is, complete segregation), contain only females.

Considering first the "male" portion of the table, each row of the table contributes to the likelihood ratio statistic in the following way:

The value of a cell in each row under independence is

$$\frac{m \cdot k_i}{N}. \tag{B1}$$

The contribution of each row to G^2 is

$$2\left[k_i \cdot \log \frac{k_i}{(mk_i/N)} + 0 \cdot \log \frac{0}{(mk_i/N)} \right] = 2\left[k_i \cdot \log \frac{N}{(m)} \right]. \tag{B2}$$

Summing over the first L rows yields

$$2\left[\sum_{i=1}^{L} k_i \log\left(\frac{N}{m}\right) \right] = 2m \log\left(\frac{N}{m}\right) \tag{B3}$$

because N / m is constant across rows and the sum of k_i equals m across the first L rows by definition. By analogy, when considering the "female" portion of the table, the following obtains:

$$2\left[\sum_{i=L+1}^{K} k_i \log\left(\frac{N}{N-m}\right) \right] = 2(N-m) \log\left(\frac{N}{N-m}\right). \tag{B4}$$

Putting both portions together and expressing totals as proportions,

$$2\left\{Np_m \log\left(p_m\right)^{-1} + \left[N\left(1-p_m\right)\log\left(1-p_m\right)^{-1}\right]\right\}, \quad \text{(B5)}$$

which simplifies to

$$2N\left\{p_m \log\left(p_m\right)^{-1} + \left[\left(1-p_m\right)\log\left(1-p_m\right)^{-1}\right]\right\}, \quad \text{(B6)}$$

where p_m is the proportion male in table.

As I previously stated, this result is exact only when each occupation row consists entirely of males or entirely of females, a property that is dependent on the marginal distributions of the table in question. Although it is possible to construct arbitrary tables in which maximum obtainable G^2 statistics are substantially lower than those that would be obtained from this formula, in most real-world distributions, the calculated results are an extremely close approximation. In fact, for the 22 sex-by-occupation tables that provide the data for the empirical application in this article, in every case, a "perfect-association" table can be formed such that each row of the table contains a 0 cell. The ability to construct such a table reflects, at least in part, the fact that there is a moderate number of occupational categories in each table, with most having 16–19 occupations. I developed a software algorithm that detects when such perfect assignment is possible.

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