THE PAST, PRESENT, AND FUTURE OF SEX SEGREGATION METHODOLOGY^{*}

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We review the logic underlying margin-free analyses of sex segregation arrays. In the course of our review, we show that the Karmel-MacLachlan decomposition does not live up to its marginfree billing, as the index upon which it rests, I_{p} , is itself marginsensitive. Moreover, because the implicit individualism of D is necessarily inconsistent with margin-free analysis, the field would do well to abandon not merely the Karmel-MacLachlan decomposition but all related efforts to purge marginal dependencies from Dinspired measures. The criticisms that Watts (1998) levels against our log-multiplicative approach are likewise unconvincing. We demonstrate that our preferred models pass the test of organizational equivalence, that the "problem" of zero cells can be solved by applying well-developed methods for ransacking incomplete or sparse tables, and that simple log-multiplicative models can be readily devised to analyze disaggregate arrays. We illustrate these conclusions by analyzing a new cross-national archive of detailed segregation data.

or all its faddishness, the concept of path dependency proves useful in understanding the history of sex segregation research, and not merely because the index of dissimilarity (hereafter, D) has shaped and defined the methodology of segregation analysis over the last 25 years. It is perhaps more important that D has been so dominant during this period that it undermined all independent conceptual development. Indeed, segregation scholars have effectively assumed that sex segregation is simply whatever D measures, and the occasional attempt at methodological and conceptual innovation has typically taken the form of better realizing the particular vision of sex segregation embodied in D. The approach that Watts takes in this issue falls within the foregoing tradition. Although this line of research (e.g., Karmel and MacLachlan 1988; Watts 1992, 1993, 1997) is a premier example of D-inspired innovation, we argue that the study of segregation is best served by

pursuing a more radical approach that is not so directly derivative of D.

There is surely no denying that D-inspired conceptualizations of segregation have surface appeal. The main implication of D and its many cousins, such as I_p , is that segregation should be measured as a proportion of the male, female, or total labor force that requires reallocation to "produce an even distribution" (White 1985:202). It is not our task here to understand the readiness with which U.S. researchers, in particular, have embraced this particular formulation, but no doubt it partly reflects their long-standing predilection for methodological individualism, as it is sometimes called. We wish to emphasize that, as a necessary cost of this conceptualization, one must conflate segregation with either the supply of female workers (i.e., the gender margins) or the pattern of labor demand (i.e., the occupation margins). This conflation has hardly gone unrecognized. Because Dinspired models are so dominant in the field, the problem has typically been addressed by attempting to revise D (e.g., Gibbs 1965) or by resorting to decompositions of various kinds (e.g., Blau and Hendricks 1979; Watts 1998). These purely reformist efforts are doomed to failure because the methodological individualism of D implies that the margins will necessarily surface.

There is, of course, no conceptual rationale that justifies muddling the study of segregation through the introduction of marginal dependencies. The underlying concept of sex segregation pertains, after all, to the joint distribution of sex and occupation rather than the component (univariate) distributions. We have suggested elsewhere (e.g., Charles and Grusky 1995) that the social forces underlying these component distributions are quite different from those underlying segregation per se. In fact, it is often argued that sex segregation is itself a function of supply or demand forces, thus rendering margin-free measurement essential insofar as scholars wish to explore this relationship empirically (see Charles forthcoming; Kanter 1977; Oppenheimer 1970; Tienda, Smith, and Ortiz 1987). The approach elaborated here involves developing models that formally distinguish between these processes and hence take on a more nearly structural form.

The above commentary might be considered superfluous preaching, as Watts apparently concedes that marginfree measures or decompositions are desirable and necessary for comparative research (p. 490). We shall begin our analysis by showing that the decomposition that Watts advocates is not margin-free, at least not in any conventional sense of the term. Further, we shall show that, insofar as

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margin-free operationalizations are sought, one must rely on measures that are simple functions of odds ratios. By implication, our own approach is effectively the only one possible, and our task here thus devolves to evaluating Watts's criticisms of our approach. In most cases, these criticisms assume that our advocacy of A is unconditional, whereas in fact we have proposed a general modeling framework that allows researchers to test and reject scalar measures of sex segregation. If attention is properly limited to models that fit, the various criticisms that Watts puts forward lose force. After elaborating the preceding points, we conclude by completing an illustrative cross-national analysis that should convince our critics that a log-multiplicative approach can be fruitfully applied to occupational arrays that are far more detailed than those previously analyzed.

CAN A D-INSPIRED INDEX BE MARGIN-FREE?

We begin by considering whether segregation scholars can indeed carry out margin-free analysis while retaining the methodological individualism of a *D*-inspired approach. It is well known that I_p is not margin-free; in fact, I_p is arguably regressive relative to D and its size-standardized variant (i.e., $D_{\rm s}$), as it depends on both margins in a segregation array rather than merely one (see Charles and Grusky 1995:933-36). At various points (e.g., p. 491), Watts owns up to this deficiency, but he subsequently ignores his own caveats by interpreting the I_P values for major occupational groups as measures of intrinsic segregation (p. 493).¹ Nonetheless, Watts clearly rests most of his hopes on a decomposition that is alleged to make margin-free analysis of trends possible. The crucial feature of this procedure, for our purposes, is that I_{P} is ultimately reapplied to both the original and rescaled tables. The resulting decomposition is accordingly no less margin-sensitive than I_p itself. Although Watts bills the Karmel-MacLachlan (KM) decomposition as margin-free, the composition effect will typically change when the margins of the Time 2 table are multiplicatively transformed (while leaving the odds ratios intact). We can conclude that the KM decomposition fails the conventional test of margin sensitivity.

This decomposition is nonetheless a step forward given that Watts apparently appreciates that odds ratios, which iterative rescaling preserves, constitute the foundation of all margin-free comparison. However, Watts does not summarize odds ratios with log-linear or log-multiplicative models; instead he resorts to an I_p index that is margin-sensitive and thus reintroduces the very dependencies that he seeks to purge. The rationale for proceeding as such, we presume, is that Watts is wed to the methodological individualism of Dand hence wishes to convert odds ratios into frequencies, thereby reintroducing the margins and undermining his initial objectives. In this sense, there is no possibility of marrying margin-free analysis with D-inspired approaches, much as Watts aspires to such. The "index wars" (Peach 1975:3) that occasionally flare up within the field proceed partly from this hopeless insistence on a comprehensive analytic solution to all questions that might possibly be entertained. We appreciate that D poses a descriptive question that interests some researchers. In this regard, D should continue to play a role in segregation research, but it must perforce be supplemented with margin-free measures when comparisons of any kind are attempted.

A MODELING FRAMEWORK

We are uninterested in becoming yet another protagonist in the latest round of index wars. There is much to be said for the high ground of elaborating a generic modeling approach that allows scalar representations of segregation to be subjected to empirical test. Although Watts represents us as unconditional advocates of A, we have been quite clear in advocating a modeling protocol rather than a particular index (Charles and Grusky 1995). The field is so index-obsessed that it was no doubt inevitable that our work would be misrepresented as simple advocacy for A. At the same time, there is at least some irony in this outcome, given that our earlier work shows that scalar formulations are not merely testable but, in most circumstances, are also easily rejected (Charles and Grusky 1995). We have reached similarly negative conclusions in our more recent empirical analyses (Charles forthcoming; Charles and Grusky forthcoming; also, see Weeden 1998). For our present purposes, it is important to review the modeling framework that yielded these results, because doing so allows us to establish that Watts's critique, which is directed at A alone, cannot convincingly be generalized to our larger approach. We shall proceed by reviewing three models that convey the flavor of a log-multiplicative framework.

The centerpiece of our approach is a multiplicative-shift model that is consistent with the conventional practice of summarizing cross-national or over-time variability in a single parameter (i.e., an index). This model takes the form:

$$n_{iik} = \alpha_k \beta_{ik} \gamma_{ik} e^{(\Phi_k Z_i \vee_j)}, \qquad (1)$$

where *i* indexes sex, *j* indexes occupation, *k* indexes context (i.e., country or period), α_k is the grand mean in the *k*th context, β_{ik} is the context-specific marginal effect for the *i*th gender, γ_{jk} is the context-specific marginal effect for the *j*th occupation, Φ_k is the multiplicative shift effect for the *k*th context, Z_i is an indicator variable for gender (i.e., $Z_1 = 0$ and $Z_2 = 1$), and v_j is the scale value for the *j*th occupation. If this specification fits the data, then Φ_k can be used to represent variability in the underlying strength of sex segregation.² We thus reject the common practice of assuming that a scalar index is empirically viable. Indeed, the frequently issued platitude that segregation indices should be selected on the basis of research interests is insufficiently stringent, as it makes no allowance for the possibility that the preferred measure fails to charac-

^{1.} The cross-occupational comparisons that Watts attempts are clouded by precisely the same marginal sensitivities that emerge when I_p is applied to historical or cross-national data.

^{2.} In the model of Eq. (1), the scale values can be identified by constraining them to sum to 0, and the marginal and shift effects can be identified by constraining the parameters for the first row, column, or level to equal 1 (see Charles and Grusky 1995:938–39).

terize the data adequately. It is high time that advocates of particular indices are held accountable for the data reduction that their indices imply.

If the model of Eq. (1) fails to fit, we can conclude that the occupation-specific contours of sex segregation (i.e., the segregation profile) are variable across contexts. The main problem with the I_p index and related *D*-inspired approaches is that qualitative differences in the segregation profile are ignored, and emphasis is instead placed on simple differences in the degree of segregation. Our models (Charles and Grusky 1995) properly refocus attention on the underlying profile itself. Although the task of modeling such profiles is not always easy, we can simplify matters for illustrative purposes by relying, without loss of generality, on the following saturated model:

$$m_{ijk} = \alpha_k \beta_{ik} \gamma_{jk} e^{(Z_i v_{jk})}.$$
 (2)

Under this specification, the scale values (v_{jk}) are now subscripted by k, thus implying that the segregation profile freely varies by context (i.e., country or period). These scale values can be used to calculate a summary index, A, that allows for qualitative variability in the underlying structure of segregation.³

We also shall consider a closely related model that estimates the net residue of segregation at the aggregate level after the data are purged of all lower-order compositional effects (see Charles and Grusky 1995:952–53). This simple multilevel model, which is saturated, can be represented as

$$m_{iik} = \alpha_k \beta_{ik} \gamma_{ik} e^{(Z_i \gamma_{jk} + Z_i \varphi_{ck})}, \qquad (3)$$

where φ_{ck} refers to the scale values for major occupational categories (indexed by c), and v_{jk} refers to the scale values for detailed occupations nested in these major categories.⁴ In estimating this model, we hope to demonstrate that our approach can be fruitfully applied to disaggregate arrays, thereby challenging Watts's more pessimistic view. The scale values under this model can also be used to define summary indices, A_{W} and A_{g} , which represent the extent of segregation within and between major occupational categories. These indices take the following form:

$$A_{W} = \exp\left(1/J \times \sum_{j=1}^{J} v_{jk}^{2}\right)^{1/2}, \text{ and}$$
$$A_{B} = \exp\left(1/C \times \sum_{c=1}^{C} \varphi_{ck}^{2}\right)^{1/2}, \qquad (4)$$

where J refers to the total number of detailed occupations, and C refers to the total number of major occupations.

EVALUATING THE CRITICISMS OF A

The next question that arises is whether the preceding framework is vulnerable to Watts's criticisms. As best we can determine, Watts is especially concerned about the sensitivity of A to occupational aggregation, particularly the seemingly benign form of aggregation in which occupations with identical sex ratios are combined. There is no disputing that A is indeed affected by benign aggregation and hence fails the test of organizational equivalence (OE). At the same time, it bears emphasizing that OE is principally important in analyses of school segregation, where the researcher wishes to ensure that cross-district variability in index values is not generated merely because the districts under study comprise differing numbers of schools (James and Taueber 1985:11). The rationale for insisting on OE is weaker in the present context because the typical comparative study of sex segregation relies on "compatible occupational definitions" (Watts 1998:490) whose constituent categories are regarded partly in realist terms. The study of occupational segregation thus takes on sociological meaning largely because occupational distinctions are regarded as socially salient. Indeed, if a realist position with respect to occupations were aggressively maintained, it would seem no more sensible to aggregate occupations than individuals.5

This line of argumentation cannot, however, be pushed too hard, if only because a purely realist position with respect to occupations is difficult to defend given incessant scholarly bickering over the appropriate dividing lines between occupations. In this context, the condition of organizational equivalence is perhaps worth insisting upon, and Watts's criticism accordingly gains force. It is reassuring in this regard that our modeling approach in fact passes the OE test when attention is properly limited to models that fit. For example, if the multiplicative-shift model of Eq. (1) holds, then the estimates of Φ_k will be unaffected by benign aggregation, as defined previously. The shift effects for this model remain unchanged because the odds ratios pertaining to the newly aggregated category are, by definition, identical to those characterizing the subcategories from which it was formed. The same conclusion holds for more complex formulations; that is, when the multiplicative-shift model is rejected and attention therefore turns to Eq. (2), benign aggregation leaves the scale values (v_{ik}) unchanged. The only caveat here is that scholars who insist on OE must impose identifying restrictions that take on the same meaning before and after aggregation (e.g., $v_{\mu} = 0$ for all k). We conclude that, with respect to an OE criterion, there is no basis for preferring the I_p index over our modeling framework.

At various points, Watts further suggests that zero cells cannot be easily accommodated within our approach, and that we are thus forced into highly aggregate analyses that "in-

^{3.} We follow Charles and Grusky (1995:945) in defining A as $\exp(1/J \times \sum v_{jk}^2)^{1/2}$. The closed-form solution for A is $\exp(1/J \times \sum \{\ln(F_{jk}/M_{jk}) - [1/J \times \sum \ln(F_{jk}/M_{jk})]\}^2)^{1/2}$, where M_{jk} and F_{jk} refer to the number of males and females in the *j*th occupation and kth context.

^{4.} The micro-level scale values (v_{jk}) are constrained to sum to 0 within each major occupational category, and the macro-level scale values (ϕ_{ck}) are constrained to sum to 0 within each context.

^{5.} In the case of sex segregation, the condition of OE is relevant not because our classification schemes vary by context, but because analysts prefer indices that yield the same trend measurements regardless of the level of aggregation. This preference is undergirded by a nominalist interpretation of occupational classifications.

TABLE 1. SOURCES AND SAMPLE CHARACTERISTICS FOR & 10-NATION DATA SET

hibit researchers from gaining insight" (p. 491). It is important to correct the common misconception that our log-multiplicative approach is fundamentally limited in this regard (see, also, Jacobs 1993:325). Although our previously published analyses have indeed rested on aggregate data, this was dictated by considerations of convenience and data availability rather than concerns about zero cells or other intrinsic limitations of our modeling framework. The methods for modeling incomplete arrays are in fact well developed. Indeed, the models outlined earlier could be readily elaborated for data arrays in which different occupations appear in different periods or countries, with the only complication being that one must carefully choose identifying restrictions that take on the same meaning for all contexts (e.g., Bishop, Fienberg, and Holland 1975:177-228; Clogg and Eliason 1987).6

We can likewise fit simple log-multiplicative models to data arrays that contain sampling zeros because of extreme segregation or sparse data. In such situations, one is naturally precluded from estimating a conventional saturated model, but nearly all formulations that allow for some form of data smoothing can be entertained. For example, the multiplicative-shift model of Eq. (1) will typically be estimable, as will various types of near-saturated models that constrain the scale values for the affected occupations to be equal across adjacent periods (or among similar countries or occupations). The fit statistics for these models will, as always, determine whether Φ_{i} or A best summarizes the data. If a near-saturated model fails to fit, we can conclude that real segregating forces are at work within the zero-celled occupations (see Weeden 1998 for a relevant application).⁷ We thus suggest that zero cells convey usable information that can be exploited by relying on well-developed methods for ransacking incomplete or sparse arrays.

AN ILLUSTRATIVE ANALYSIS

As noted previously, Watts suggests that our approach is appropriate only for highly aggregate arrays, presumably because the problems of sparse data and zero counts can be addressed through aggregation.⁸ This reasoning leads Watts to propose a methodological division of labor whereby I_p becomes the method of choice for trend analysis, whereas Ais favored for cross-national research. The logic underlying this conclusion is never fully elaborated, but Watts evidently believes that A is usable for cross-national analysis because the available data are typically in such aggregate form that the usual problems of sparseness and zero counts effectively disappear.⁹ It would surely be convenient to

Country	Census Year	Sample Size	Percent Female			
Belgium	1991	3,418,512	39.8			
France	1990	900,255	43.0			
West Germany	1993	128,912	41.2			
Italy	1991	21,071,282	35.7			
Portugal	1991	4,037,130	40.5			
Sweden	1990	4,059,813	48.6			
Switzerland	1990	3,076,445	38.0			
United Kingdom	1991	2,405,091	44.3			
United States	1990	1,152,885	45.7			
Japan	1990	12,220,974	39.8			

ratify such a compromise division of labor and thereby satisfy all parties. We are, however, reluctant to accept this compromise, not merely because the I_p decomposition is margin-dependent and hence flawed for both cross-national and over-time comparisons, but also because our modeling framework is readily applied to disaggregate data. In this section, we substantiate the latter claim by analyzing a new archive of carefully harmonized and highly detailed data from 10 industrial market economies.

We shall proceed with a 64-category occupational classification that relies heavily on recent efforts of the National Statistical Institutes of the European Union to establish a single harmonized variant of the 1988 International Standard Classification of Occupations (ISCO-88; see Charles and Grusky forthcoming for a detailed list of occupations composing this classification). The resulting classification, dubbed ISCO-COM, has garnered widespread support within the European Union, but most member countries have not yet published sex segregation arrays based on the new protocol. We have nonetheless moved forward by (a) commissioning national statistical agencies to process individual-level census data as mandated by ISCO-COM, (b) securing highly detailed segregation arrays and recoding them in accord with such translation keys as are presently available, or (c) developing our own translation keys and applying them to detailed segregation data (see Table 1 for details). By virtue of ISCO-COM, it becomes feasible to standardize more rigorously than was heretofore possible, but some misclassification inevitably remains because of inadequate detail in the indigenous schemes or because of real cross-national variability in the division of labor (Elias and Birch 1993, 1994). These errors in coding, classification, and aggregation are addressed elsewhere in more detail (Charles and Grusky forthcoming).

We begin our analysis by asking whether the underlying pattern of cross-national variability can be adequately summarized with a single parameter pertaining to the strength of segregation. If the model of Eq. (1) is applied to our 10-nation array, we find that only 14% of the total cross-national

^{6.} These methods assume, of course, that the zero entries are structural in origin.

^{7.} We assume here that zero entries arise from sampling variability. If empty cells are instead treated as structural, then standard methods for the analysis of incomplete arrays can be applied.

^{8.} These problems are, of course, best addressed not by aggregation but by estimating models of the kind discussed in the preceding section.

^{9.} The I_p decomposition is especially unwieldy for cross-national analysis because it yields $[N \times (N-1)]/2$ pairwise contrasts (where N refers to the number of countries).

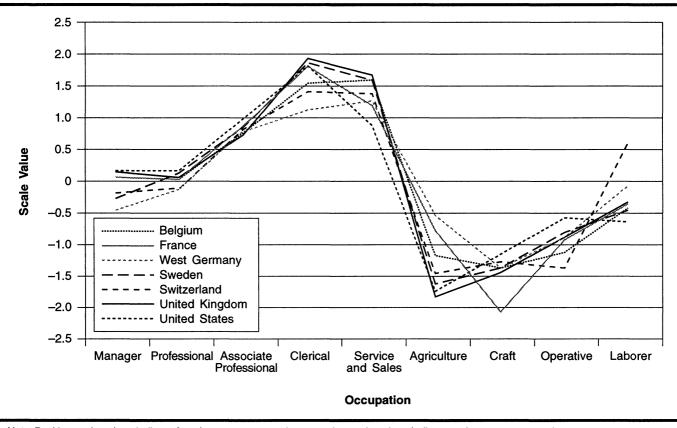


FIGURE 1A. AGGREGATE PROFILE FOR EXTREME SEGREGATION PATTERN

Note: Positive scale values indicate female overrepresentation; negative scale values indicate male overrepresentation.

variability in sex segregation is explained, with the remaining variability attributable to cross-national differences in the segregation profile. The latter result admits of two possible interpretations: We can conclude either that (a) national values, policies, and institutions have occupation-specific effects (e.g., occupationally targeted affirmative action), or that (b) segregation is driven not by national variables but by local occupation-specific forces (e.g., occupation-specific cultures, union practices). These interpretations are consistent with our premise that *D*-inspired approaches should be supplemented with more careful study of segregation profiles.

Although the preceding results suggest that cross-national variability at the detailed level cannot be characterized simply, a deeper commonality may obtain at the aggregate level of major occupational groups. We can test this hypothesis by fitting a model that estimates the net residue of segregation at the aggregate level after purging the data of lowerorder compositional effects (see Eq. (3)). The macro-level estimates from this model, as graphed in Figures 1a and 1b, indeed reveal a rather striking similarity in the underlying segregation curves. In characterizing these figures, we suggest that sectoral and gradational principles are simultaneously at work, with the former principle accounting for the crowding of women into the nonmanual sector and the latter accounting for the tendency of men to dominate the most desirable occupations in both the manual and nonmanual sectors (i.e., managerial and craft occupations). The observed commonalities can be attributed, then, to primitive segregating principles that are operative in all societies but expressed to varying degrees (compare Figure 1a and 1b). In this regard, advanced industrial segregation does have a deep structure, albeit one that emerges only when all micro-level variability is stripped away.

The micro-level estimates from our model are next graphed in Figure 2. As might be anticipated, the scale values for virtually all occupations are widely scattered, thus suggesting that the forces of micro-level segregation manifest themselves in highly variable ways. The segregation of detailed occupations may reflect such idiosyncratic processes as (a) the types of firms, industries, or occupations that served as models for hiring practices when the occupation was established or expanded, (b) the closure strategies (e.g., unionization, credentialling) that occupational incumbents seized upon in attempting to monopolize skilled tasks, (c) the "women-friendliness" of the owners, unions, and managers involved in occupational staffing and recruitment, and (d) the gender composition of the labor force when the occupation expanded and car-

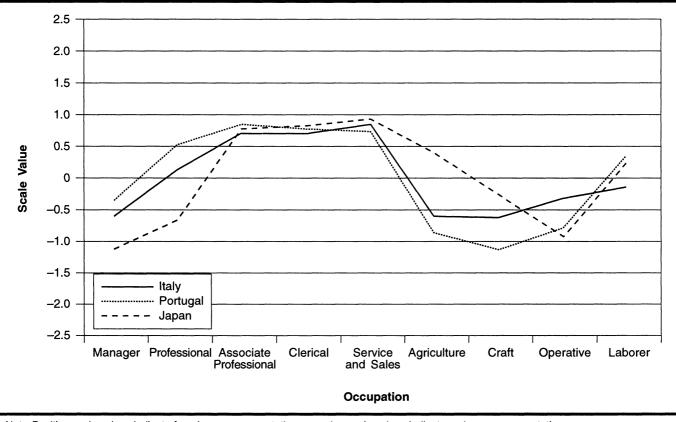


FIGURE 1B. AGGREGATE PROFILE FOR MODERATE SEGREGATION PATTERN

Note: Positive scale values indicate female overrepresentation; negative scale values indicate male overrepresentation.

ried out its formative recruiting. These processes suggest a form of path dependency whereby local and particularistic forces influenced the initial gender-typing of occupations and definitively shaped the subsequent trajectory of development (Stinchcombe 1965; Weeden and Sørensen forthcoming). 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 (Charles and Grusky forthcoming).

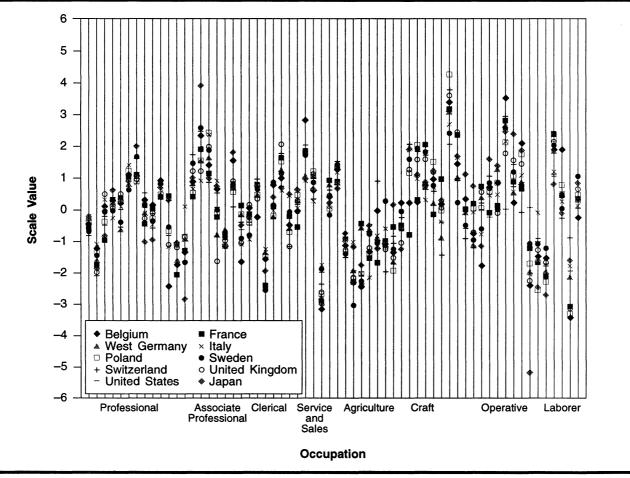
The foregoing results make it clear that all sex segregation indices, conventional or otherwise, are inadequate for the present data. If summary measures are insisted upon, we would do well to rely on A_B and A_W and thereby distinguish between segregation at the detailed and major occupational levels (see Table 2). When these indices are applied to our data, we find that they correlate only weakly, with r registering as low as .09 for the full 10-nation sample.¹⁰ Although some countries in our sample have uniformly weak segregation at both levels (e.g., Italy), others combine strong withincategory segregation with virtual integration at the macro level (e.g., Japan). The latter results should give pause to scholars who have been emboldened to interpret the wellknown parallel-lines thesis (e.g., Jacobs and Lim 1992) as providing more general license for highly aggregate crossnational analysis. Of course, our results cannot speak directly to the thesis in its original form, as we lack the historical data needed to determine whether A_{μ} and A_{μ} track over time. The present evidence suggests, however, that a cross-sectional analogue to the parallel-lines thesis cannot be safely advanced, given that A_{μ} and A_{μ} are only weakly correlated and that inspection of either therefore conveys limited information on the other. This result again suggests that segregation systems are only loosely coupled at the detailed and aggregate levels. The deep structure of macro-level segregation may arise from the interleaving of fundamental sectoral and gradational forces, whereas the chaos of micro-level segregation evidently reflects the more haphazard effects of union arrangements, the particular timing of expansionary pressures, and similar local institutional forces.

CONCLUSIONS

As generous as it is, we are disinclined to accept the compromise settlement that Watts offers, given that our modeling

^{10.} This correlation increases somewhat (r = 0.44) when Japan is excluded from our sample.

FIGURE 2. CROSS-NATIONAL DISPERSION IN PURGED SCALE VALUES



Note: Positive scale values indicate female overrepresentation; negative scale values indicate male overrepresentation.

framework can be straightforwardly elaborated to allow for disaggregate analysis over time and across nations. The great virtue of our framework, so extended, is that the net residue of segregation can be teased out at multiple levels of analysis. In the present case, we find that macro-level variability has a simple and lawful character, whereas micro-level variability surely does not. We have also defined two new indices, A_w and A_p , that permit analysts to decompose the total amount of segregation into components generated within and between major occupational categories. The generative forces underlying segregation evidently differ by level, because A_{w} and A_{μ} correlate only weakly across the 10 countries in our sample. The main methodological conclusion to be drawn is that D-inspired indices, such as I_p , cannot represent the complex qualitative differences in sex segregation that may emerge when disaggregate data are analyzed.¹¹

We cannot imagine that Watts truly wishes to suppress such results and rely exclusively on summary measures. By contrast, we readily allow that D should play a supporting role in segregation analysis, if only for reasons of consistency with prior work. Although the analytic question that Dposes clearly has some appeal, we are hard-pressed to identify any rationale for continuing to use I_p , D_s , and related Dinspired indices and decompositions. Indeed, although these approaches are advertised as margin-free, they ultimately fail to deliver (see Charles and Grusky 1995:935). In the present case, the KM decomposition is flawed because the index upon which it rests, I_p , is dependent on both margins in a sex-by-occupation array. There is no possibility of a quick fix that renders D or its close cousins margin-free. We have shown that, insofar as margin-free comparisons are insisted upon, segregation analysts must perforce rely on odds ratios and simple functions thereof.

As we see it, the only fallback for Watts is to insist that segregation is whatever D or I_p measures, thereby forgoing all pretense of independent conceptualization. If this nomi-

^{11.} The available evidence suggests that largely similar results obtain when trend analyses are carried out (see Weeden 1998).

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TABLE 2. SCALAR MEASURES OF OCCUPATIONAL SEX SEGREGATION APPLIED TO A 10-NATION DATA SET

	Segregation Index			
Country	D	Α	A _B	A _w
Belgium	51.2	6.10	2.82	4.45
France	54.5	6.10	3.08	3.78
West Germany	50. 9	4.50	2.38	3.29
Italy	43.0	3.31	1.76	2.92
Portugal	47.7	5.26	2.12	4.26
Sweden	60.2	5.47	3.18	3.77
Switzerland	55.5	5.52	2.92	3.89
United Kingdom	56.5	6.28	3.41	4.30
United States	45.1	4.39	2.91	3.12
Japan	44.8	5.87	2.13	5.12

Note: D =Index of Dissimilarity; A =Association Index; $A_{g} =$ Between-Category Association Index; $A_{w} =$ Within-Category Association Index.

nalist position is taken, one must immediately abandon the standard assumption that segregation should be measured independently of both the supply of female workers and the structure of labor demand. It is precisely this assumption, however, that underlies decades of reformist tinkering directed toward eliminating the extraneous marginal dependencies that plague *D*-inspired measures. The field has thus long embraced margin-free conceptualizations of sex segregation (e.g., Abrahamson and Sigelman 1987; Blau and Hendricks 1979; Fuchs 1975; Gross 1968). In this sense, our log-multiplicative framework rests on a traditional definition of segregation, but unlike other measures and approaches, it succeeds in operationalizing such a definition faithfully.

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