Major “Combination-Patterns” of Residential Segregation Based on Five Dimensions of Segregation: Latent Profile Analysis

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*More results will be available in the next few months.

ABSTRACT
Literature on residential segregation has traditionally focused on using just two domains of segregation, evenness and exposure, while making less use of concentration, centralization, and clustering. When studies do invoke all five dimensions of segregation, discussions have typically centered on "hypersegregation"—a pattern in which all five measures of segregation domains are simultaneously high. Nevertheless, studies suggest distinct consequences (e.g., crime rate, mortality, etc) associated with a large array of non-hypersegregated combination-patterns of residential segregation. This paper attempts to get a clearer purchase on what combination-patterns of residential segregation exist in the U.S. and what meanings we are to make of these patterns. Based on 380 metropolitan areas (US Census 2000), I use Latent Profile Analysis—a class of finite mixture modeling—to reduce 380 unique combination-patterns of segregation into an essential few for blacks, Hispanics, and Asians. This study shows that all integrated cities are alike but that segregated cities are segregated in their own but few dominant ways.

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INTRODUCTION

In the late 1980s, Massey and Denton (1988) helped settle controversies concerning the ways of measuring residential segregation by taking stock of twenty or so segregation indices in the literatures and trimming them down to a few essentials. Using factor analysis, they empirically verified five distinct dimensions of segregation (evenness, exposure, concentration, centralization, and clustering) that were theoretically conceived, and singled out the best indices that correspond to each dimension. In so doing, they underlined the salience of investigating segregation in terms of the dimensions beyond just the usual ones, typically evenness or isolation. Specifically, they underlined the importance of considering the patterns of segregation based on different *combination* of the five dimensions of segregation.

Since then, just one combination-pattern in particular has garnered much of attention: hypersegregation pattern, which represents high segregation measures on all five dimensions. Massey and Denton (1989; 1993), for example, showed that blacks were more likely to experience hypersegregation than are Hispanics. Wilkes and Iceland (2004) reconfirmed Massey and Denton's 1989 findings, showing that more metropolitan areas were hypersegregated for blacks than for Hispanics, Asians, or Native-Americans.

However, except for the hypersegregation pattern, relatively little attention has been paid to other patterns of mix among the five dimensions of residential segregation. There is no clear purchase on what combination-patterns of segregation exist in the U.S. cities, and what meanings we are to make of these patterns. Nevertheless, there have been studies that are suggestive of a large array of different combination-patterns (Massey & Denton 1989; Wilkes & Iceland 2004), as well as distinct consequences of these patterns (Shihadeh & Flynn 1996; Collins & Williams 1999; Wagmiller Jr 2007; Eitle 2009; Xie 2010). However, studies have not yet attempted to systematically classify these varying individual patterns of segregation into meaningful categories. This paper believes that there is a need to establish a formal typology for the patterns of residential segregation.

Thus far, any sort of typological analyses in the segregation literature have typically focused on reducing the complexities of segregation *measures*, not segregation *patterns* (Massey & Denton 1988; Johnston, Poulsen, & Forrest 2007). These typological studies on segregation measures have been useful, as they have provided the field with a uniform set of indices for measuring different aspects of segregation. Using these indices, this paper attempts to reduce the complexities of combination patterns of segregation into a *few essential* categories/types, whose meanings can later be explored.

Toward this end, I conduct a type of finite mixture modeling—latent profile analysis (LPA)—on 380 metropolitan areas of the United States, based on the data from 2000 US Census. The findings from this analysis will inform us: (1) What combination-patterns of segregation exist in the U.S. cities? (2) Which combination-patterns of segregation does each city follow? (3) How do these segregation patterns vary across blacks, Hispanics, and Asians? (4) What are the major attributes of these combination-patterns—i.e., how do the city-specific characteristics relate to the distinct patterns of segregation? (5) What are the distinct consequences of these combination-patterns? The paper's results are expected to show that all integrated cities might be alike but that segregated cities are segregated in their own but few dominant ways.

LITERATURE REVIEW

Dimensions of Residential Segregation

Segregation is defined as the "differences in the distribution of social groups, such as blacks and whites, among units of social organization" (James & Taeuber 1985:4). Residential segregation refers to the differences in the distribution of social groups across the units of residential area.

Index controversy. Though seemingly simple in definition, residential segregation has been anything but a simple concept to operationalize (cf. see the review in Massey & Denton 1988). Prominent scholars have attested to this difficulty, dating back several decades. Duncan and Duncan (1955), while introducing the very popular segregation measure—dissimilarity index—, professed the need to cover the spatial aspect of residential segregation that their dissimilarity index could not address. Taeuber and Taeuber (1969:197), likewise, dismissed the notion of a single comprehensive measure of segregation, asserting that "any single index of such a complex phenomenon [as segregation] is an arbitrary over-simplification of reality" (p220).

Ironically enough, despite the early professed limitation of single index approach by Duncan and Duncan (1955) and others, the residential segregation literature in the 1960s and 70s had largely relied on using just a single index—dissimilarity index—and generally ignored other measures of segregation (cf. see the review by Winship 1977). Beginning in the late 70s, however, scholars began critiquing the single index approach to segregation study and ushered in an era of contentious debates on the measures of segregation (cf. see the review by James and Taeuber 1985; Massey & Denton 1988).

At the time Massey and Denton published *Dimensions of Segregation* in 1988, the field of segregation was said to be at a "state of disarray" with no consensus on how to measure segregation:

> "The field of segregation studies is presently in a state of theoretical and methodological disarray, with different researchers advocating different definitions and measures of segregation. There is little agreement about which measure is best to use and under what circumstances. Studies using inconsistent segregation measures are multiplying" (Massey & Denton 1988:282).

Such a situation entailed some troubling consequences, including researchers' picking segregation indices "arbitrarily" with "no clear reason to prefer one index over another" or researchers' resorting to just using a "measure that is currently popular" (James & Taeuber 1985:2).

Five dimensions of segregation. To help resolve this problem, Massey and Denton took stock of 20 measures/indices of segregation that were popular in the literature and classified the indices into five broad groups suggested by the literature. Then, based on the 1980 census data from 60 large metropolitan areas of the U.S., Massey and Denton conducted factor analysis to test whether these five groups were empirically distinct as well. They found the 20 segregation indices to "hang together" in the way that supported the theoretical distinction of the five groups. And based on the results from the factor analysis, Massey and Denton selected a single index for each group that best distinguished the particular group from the rest. At the end of the exercise, a great deal of the complexity of segregation was systematized, with 20 segregation indices trimmed to five indices, each representing five distinct dimensions of segregation: (1) evenness, (2) exposure, (3) concentration, (4) centralization, and (5) clustering (See Appendix for the detailed description of each of the five indices).

Combination-Patterns of Five Dimensions of Segregation

Massey and Denton (1988) urged researchers to view residential segregation as multidimensional phenomenon. They directed researchers' attention to particularly looking at *combination-patterns* of segregation. Massey and Denton (1988) suggested that not only does each dimension of segregation entail distinct social consequence but that mix or combination of different dimensions of segregation could bring distinct consequences. In this regard, they cautioned researchers not to solely focus on just one combination-pattern that is obvious in its salience—the hypersegregation pattern, defined as having high segregation measure on all five dimensions—but to pay attention to other combinations as well:

> "Researchers interpret the constellation of outcomes on the five spatial dimensions as segregation, but this interpretation is an abstraction of empirical reality, not reality itself. Groups may be separated from one another in many different ways, corresponding to various combinations of the five distributional characteristics" (Massey & Denton 1988:283).

Hypersegregation pattern. With that being said, Massey and Denton's next project in 1989 brought a lot of attention to precisely the combination-pattern that they singled out: Hypersegregation. In the study, Massey and Denton (1989) postulated that segregation in multiple dimensions create worse consequences than segregation in just one dimension because the problems related to segregation tend to multiply across dimensions. As such, segregation problems for blacks, especially *urban* blacks, tend to be understated because blacks, in comparison to other minority groups, are said to experience higher levels of segregation not only in one dimension but across all five dimensions. Using 1980 US census data on 60 largest standard metropolitan statistical areas (SMSAs), they showed that the number of SMSAs with the combination-pattern of segregation with all five dimensions at a "high" segregation level were significantly higher for blacks than for Hispanics. Massey and Denton (1989) found six SMSAs to be hypersegregated for blacks—Baltimore, Chicago, Cleveland, Detroit, Milwaukee, and Philadelphia—, while none for Hispanics. For Hispanics, none of the SMSAs were found to have high segregation on even just four dimensions.

These findings were generally reaffirmed by Wilkes and Iceland (2004), who used 2000 US Census data on 318 metropolitan areas. Wilkes and Iceland found six metropolitan areas to be hypersegregated for blacks—Chicago, Cleveland, Detroit, Milwaukee, Philadelphia, and Newark—, while none for Hispanics and Asians. They also found 29 metropolitans areas to be segregated on four dimensions for blacks, while two for Hispanics and none for Asians. Based on these results, Wilkes and Iceland (2004) concluded that "our research affirms Massey and Denton's (1989) claim that blacks are especially disadvantaged in U.S. metropolitan areas" and that "the hypersegregation of blacks remains common enough to warrant continued attention" (p34).

Non-hypersegregation patterns. What about other combination-patterns of segregation? We know from Massey and Denton's (1989) that six out of 60 large SMSAs were hypersegregated and that these six SMSAs included nearly a quarter of entire black population in the country. But, in the same study, "other" patterns were discussed but merely to indicate the non-hypersegregated patterns; and, the description of other patterns only went to the extent of how many dimensions were segregated or not segregated, without information on the precise mix of all five dimensions together. In other words, beyond the dichotomization of hypersegregation vs. non-hypersegregation distinction, no further categorization of segregation patterns was made.

Why "other"combination- patterns matter. The lack of clear description and conceptual distinctions within the "other" combination patterns is troubling given the fact that studies have demonstrated that segregation patterns can matter beyond just the hypersegregation pattern. For example, Shihadeh and Flynn (1996) examined the homicide and robbery records by blacks for the U.S. cities and found that residential segregation in terms of unevenness did *not* affect black violence if unevenness did not accompany *isolation*, thus suggesting that a distinct combination of unevenness and isolation can entail unique consequences. In another study, Collins and Williams (1999) found that *isolation* significantly affects black mortality but its impact is greater in the cities with high unevenness, implying that different mix of unevenness and isolation is consequential. In terms of joblessness, Wagmiller Jr (2007) found that jobless men tend to reside in cities that are high on *clustering, concentration, and isolation*, but, for jobless blacks, they tend to reside in cities that are high on *four* dimensions: clustering, concentration, isolation, *and centralization*. Wagmiller Jr's (2007) findings suggest that a combination of clustering, concentration, isolation, and centralization matter greatly for black joblessness, but, for Hispanics and Asians, *centralization* was a less important part of the segregation combination. Finally, two studies investigated impacts of concentration and centralization on black homicide victimization. Eitle (2009) found that four of the five dimensions of segregation (unevenness, isolation, concentration, and centralization) had significant association with black homicide victimization. But, he also found that when combining the five dimensions into two, with one group representing "separation" (*unevenness, isolation, and clustering*) and another representing "location" (*concentration and centralization*), the black homicide victimization depends only on the "location" combination—i.e., concentration and centralization. In contrast, Xie (2010) who used the same dataset as did Eitle (2009) but with more extensive control variables, found both "location" *and* "separation" combinations to be significantly associated with black homicide victimization. All together, these studies and others attest to the need to examine residential segregation along multiple dimensions but, more importantly, to extend such examinations to the combination-patterns of segregation beyond just the hypersegregation pattern.

Taxonomy of Patterns of Residential Segregation. There is a need to get a clearer purchase on how cities in the U.S. are segregated in terms of different combination of the five dimensions of residential segregation. Even for hypersegregation pattern, the measurement criteria have been somewhat crude with the use of 0.6 as the typical cut-off value for much of the indices (cf. see Massey & Denton 1989; 1993). There is a possibility that even within the hypersegregation pattern more essential distinctions could be found—e.g., super (?) hypersegregation. For these reasons, this paper believes that a classification that sorts (or reduces) numerous individual patterns of residential segregation into a few essential patterns is needed. Such a classification is likely to offer a useful conceptual map to view, interpret, and think about individual city's segregation. To this end, this paper takes a first small step; we conduct latent profile analysis to distinguish 380 metropolitan areas in the U.S. into a few essential groups characterized by the most dominant combination patterns of residential segregation. But, first, a brief word about the relevance of classification and typological exercises in social science in general.

Typologies have been an analytic tool widely used in social science (cf. Weber's (1978) exposition on "ideal-types"). As some say, "classifying complex objects into some smaller number of categories is fundamental to the scientific enterprise (Ahlquist & Breunig 2012:92).

Typologies “make crucial contributions to diverse analytic tasks: forming and refining concepts, drawing out underlying dimensions, creating categories for classification and measurement and sorting cases” (Collier, LaPorte, and Seawright 2012: 217). Classes or categories in typological identification can either describe the “phenomenon under analysis” (i.e., descriptive) or the outcomes being explained by some explanatory variables (i.e., explanatory). For this paper, the typologies of the patterns of residential segregation is primarily intended to be descriptive, but it can also be considered for “explanatory” purpose when we associate relevant city-characteristics (such as crime rate, joblessness, and mortality) to the segregation patterns.

HYPOTHESES

There are several expected findings based on the review of the literature.

Hypothesis 1. There exists a combination-pattern of segregation that represents the “worst” type—i.e., the hypersegregation pattern (i.e., high segregation on all five dimensions); however, this type exists only for blacks and not for Hispanics and Asians.

Hypothesis 2. There exists a combination-pattern of segregation that represents the “best” type—i.e., *low* segregation on all five dimensions; however, the proportion of cities belonging to this type will be

Hypothesis 3. In between the “worst” and the “best” types of segregation patterns, there exist numerous other combination-patterns of residential segregation that are unique and have distinct shapes. These intermediate types of segregation patterns differ across race in terms of both the quantity (i.e., how many distinct intermediate types there are) and the qualities (i.e., what are the shapes/magnitudes of patterns for each type).

> *Hypothesis 3a.* Based on Wilkes and Iceland’s (2004) and Johnston et al. (2007), the combination-pattern of high segregation on *unevenness, isolation, concentration*, and *centralization* emerges as one of the segregation pattern type for blacks but not for Hispanics.
>
> *Hypothesis 3b.* Based on Massey and Denton’s (1989), the combination-patterns that involve high segregations in *concentration* and *centralization* emerge as more dominant patterns for blacks than for Hispanics.

Hypothesis 4. Most types of segregation patterns (including the intermediate types) entail distinct antecedents (e.g., average educational attainment level, income, occupational context, etc) and consequences (e.g., average crime rate, joblessness, mortality, etc).

> *Hypothesis 4a.* The hypersegregation is the most deleterious type of combination-patterns, but, depending on particular outcomes examined (e.g., mortality vs. crime rate), “other” types are just as deleterious as the hypersegregation type.

****THESE TWO HYPOTEHSES (4 and 4a) WILL BE TESTED WHEN I GET ACCESS TO THE NECESSARY DATA LATER THIS YEAR*****

Hypothesis 5. All integrated cities are integrated alike but all highly segregated cities are segregated in their own ways. That is, the “best” types of segregation patterns are similar in magnitudes and shapes across race but the “worst” type and some intermediate types of segregation patterns are more distinctive in magnitudes and shapes across race.

Hypothesis 6. The cities that belong to each type of combination-patterns of residential segregation are distinct across race (i.e., the cities that belong to the “worst” type of segregation patterns for blacks are not necessarily the same cities that belong to the "worst" type for Hispanics.)

DATA & METHOD

My data consists of 380 U.S. metropolitan areas—the boundaries of which are defined by the Office of Management (OMB) as of June, 1999—and five dimensions of segregation measures, represented by Dissimilarity (D) for unevenness, Isolation (xPx) for exposure, Absolute Concentration Index (ACO) for concentration, Absolute Centralization Index (ACE) for centralization, and Spatial Proximity (SP) for clustering. (See the Appendix for the detailed descriptions). Census tract is used as the basic area unit. The minority race-ethnic groups consist of blacks, Hispanics, and Asians. All data comes from the website provide by U.S. Census Bureau's Housing and Household Economic Statistics Division.[1]

*************During next few months, I also plan to use the following data for examining the antecedents and consequences of the segregation patterns. For the data on the consequences, I plan to use Uniform Crime Report (UCR) to obtain information on homicide and robbery rates in the U.S. cities, National Center for Health Statistics' (NCHS) U.S. Mortality Detail Files for information on mortality rates, Neighborhood Change Database (NCDB) for information on joblessness, and National Vital Statistics System (NVSS) for information on homicide victimization. For the data on the antecedents, I plan to use US Census Bureau's 2000 Census Summary File 1. I plan to link these datasets to my current data on segregation measures.*******

Dependent variable

The dependent variable is the vector of five segregation measures (D, xPx, ACO, ACE, and SP) for each metropolitan area. These five measures are continuous and are the manifest indicators for the unobserved latent class, which represents the "type" of segregation combination-patterns we are trying to find. These latent classes are the nominal values of a single latent categorical variable: "Segregation Pattern".

Distal Outcomes

The distal outcome variables are the "outcome" variables that use the latent categorical construct ("Segregation Pattern") as the explanatory variable. These outcome variables include the measures of: (1) homicide and robbery rate, (2) mortality, (3) joblessness, and (4) homicide victimization.

*****************I am currently debating whether to include these dependent variables as a part of the overall estimation model (i.e., combine both the measurement and explanatory parts of the structural equation modeling), or to treat the two models separately and analyze the outcomes of segregation patterns by using the contingency table analysis (e.g., log-linear).*****

Antecedent (or Control) Variables

The control variables are used as explanatory variables that explain the variations in the latent categorical variable ("Segregation Pattern"). Because the control variables do not vary by individual latent classes, they are *not* equivalent to the latent variable's indicators—which are the vector of five segregation measures. The control variables include the city's population size, racial composition, and median income.

[1] http://www.census.gov/hhes/www/housing/housing_patterns/gettable_msa.html

ANALYTIC STRATEGY

Latent profile analysis (LPA) is a type of finite mixture modeling that is akin to latent class analysis (LCA), except that dependent variables of LPA are continuous while those of LCA are categorical (Muthen 2001; Muthen and Shedden 1999).

Both LPA and LCA use Expectation-Maximization (EM) algorithm based on maximum likelihood estimations with the same set of unknown parameters (see Muthen & Shedden 1999 for detailed review). Only difference is the distributional assumption of the manifest indicators. Since it is more intuitive to describe the method in terms LCA, I briefly explain LPA by showing the logic behind LCA. Specifically, I show the unconditional LCA model with no control and distal outcomes involved (see Dayton 1999).

Estimation procedure

I want to find whether there exist distinct types of segregation patterns based on different combination of the five measures of segregation indices. To do so, I employ latent class analysis (LCA). LCA recognizes the patterns of the segregation measures across cities and group these cities together according to the similarity in the patterns of measures. Theses patterns are assumed to be a function of an unobserved latent categorical variable, which represents the "Segregation Pattern."

With the five segregation measures, one example of an outcome vector might be the no-segregation on all five dimensions: {0,0,0,0,0}. Another outcome might be segregation on all five dimensions: {1,1,1,1,1}. Let y be such an outcome vector. Then, the *conditional probabilities* of *y* for a segregation score *i*,*j*,*k*,*l*,*m* (either 0 or 1) for segregation index 1, 2, 3, 4, and 5—representing D, xPx, ACO, ACE, and SP respectively—, given an unobserved latent class *c* (or the nominal "type" of the Segregation Pattern) is

$$P(\mathbf{y} \mid c) = \pi_{ic}^{y1}\ \pi_{jc}^{y2}\ \pi_{kc}^{y3}\ \pi_{lc}^{y4}\ \pi_{mc}^{y5}$$

For example, the conditional probability of $\mathbf{y_w}$={0,0,0,1,1} given a latent class *c* for the city *w* is:

$$P(\mathbf{y_w} \mid c) = \pi_{0c}^{y1}\ \pi_{0c}^{y2}\ \pi_{0c}^{y3}\ \pi_{1c}^{y4}\ \pi_{1c}^{y5}$$

The key assumption here is that each conditional probability π_{ic}^{y} is independent of other conditional probabilities π_{jc}^{y}'s *given* that their latent class is accounted for. From the above, we can see that the *unconditional* probability of $\mathbf{y_w}$={0,0,0,1,1} across all latent classes *c* (from 1 to T) would be:

$$P(\mathbf{y_w}) = \sum_{c=1}^{T} \pi_c\ \pi_{0c}^{y1}\ \pi_{0c}^{y2}\ \pi_{0c}^{y3}\ \pi_{1c}^{y4}\ \pi_{1c}^{y5}$$

where π_c represents the proportion of cities in class *c*. Finally, from the two equations above and using Bayes' theorem, we can derive the posterior probability of class membership given the vector of outcomes. For example, the posterior probability of belonging to the latent class *c*, given the vector $\mathbf{y_w}$ is:

$$P(c \mid \mathbf{y_w}) = \frac{P(y_w \mid c)\,\pi_c}{P(y_w)}$$

Based on the expressions above, we construct the likelihood function *L* and use EM algorithm (Muthen & Shedden 1999) to estimate the unknown parameters, π_c and π_{ic}^{y}'s, based on the observables ***y's***. And, for conditional models that include control and distal outcome variables, we include these variables as one of the observables in the appropriate parts of the equations above. All computations are made using Mplus 6.0

The below is the conceptual path diagram of our model:

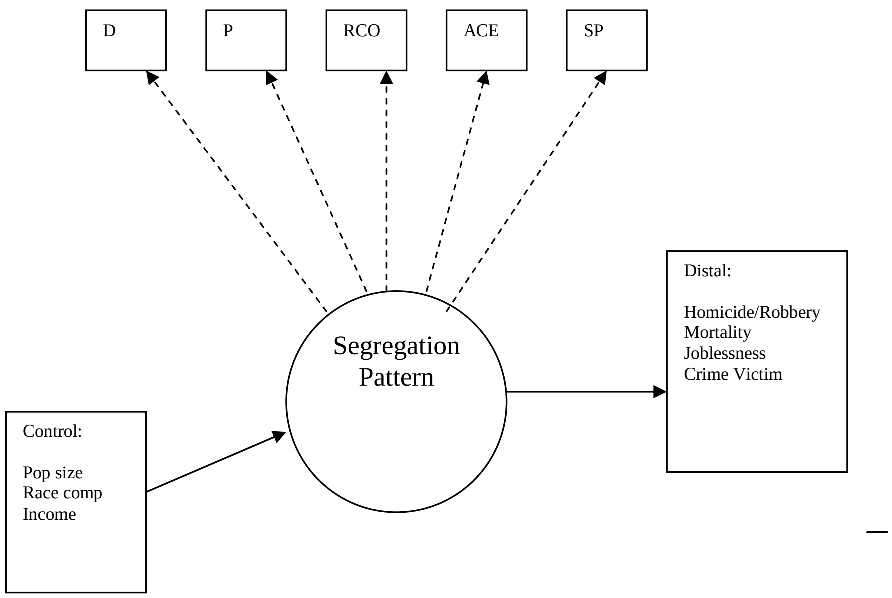

Figure 1. Conceptual Path Diagram for Latent Profile Analysis of Residential Segregation Patterns.

Preliminary Results

Blacks

For blacks, eight distinct combination-patterns of residential segregation are identified, using the model selection criteria of adjusted BIC and entropy (Muthen 2001; Petras et al. 2010). Table 1 presents these eight combination patterns, with the average segregation values and the class sizes. As Table 1 shows, "c5" represents the "worst" combination-pattern of segregation for blacks, with the average value of each segregation index at the highest or near highest (0.800, 0.769, 0.949, 0.715, and 1.00). This class comprises of six cities (data not shown here): (1) Chicago-Naperville-Joliet, IL, (2) Cleveland-Elyria-Mentor, OH, (3) Detroit-Livonia-Dearborn, MI, (4) Milwaukee-Waukesha-West Allis, WI, (5) New Haven-Milford, CT, and (6) Philadelphia, PA. These cities are the same six "hypersegregated" cities identified by Wilkes and Iceland (2004) except for New Haven-Milford, CT. Wilkes and Iceland (2004) found Newark, NJ as one of the six "hypersegregated" areas instead of New Haven-Milford, CT. In this paper's findings, Newark, NJ belongs to the second "worst" class (c1).

The "best" combination-pattern for blacks is a toss-up between c6 and c8. If evenness and isolation are considered more important, then c6 is the best class. This class consists of 121 cities and includes such cities as Binghamton, NY, Boulder, CO, Idaho Falls, ID, and Fargo, MN. Figure 2 shows the chart of eight combination-patterns of residential segregation for blacks.

Though the patterns look similar across eight classes (mostly a tilted "W" shape), class partition is highly distinct. That is, a city's probability of belonging to its most likely latent class (e.g., Philadelphia's likelihood of belonging to c5) is far greater than its probability of belonging to any of other seven latent classes. Table 4 shows the average probabilities of most likely latent class membership. For example, for those cities whose most likely latent class membership is c1, their average probability of belonging to c1 is 0.96. The remaining classes all have 0.9 or above average probabilities of most likely latent classes, suggesting a distinct partitioning.

Of the eight combination-patterns for blacks (Figure 2), one combination-pattern (c7) is particularly distinct in its shape. Unlike other classes, c7 does not have a "W" shape but rather a straight line shape. The cities in c7 have unexpectedly *low* level of concentration, while unexpectedly high levels of isolation and centralization. This class consists of 14 cities (Table 7), including Richmond, VA, Tuscaloosa, AL, Jackson, MS, Baton Rouge, LA, and Memphis, TN. Some other classes that have unconventional combination-patterns are c2 and c8 (Figure 7). [It will be interesting to see how these cities are related to various city outcomes, such as crime rates, mortality, joblessness, etc.]
***************The association between these eight combination-patterns with antecedents (average income, educational attainment, occupational status, population size, etc) and consequences (crime rate, mortality, joblessness, etc) will be analyzed in the next few months when I finish linking the datasets***

Hispanics
For Hispanics, five combination-patterns of residential segregation are identified. The "worst" class is c5 (Table 2). The 16 cities in this class include Fresno, CA, Los Angeles, CA, San Antonio, TX, Savannah, GA, Essex County, MA, Philadelphia, PA, Newark, NJ, etc. The "best" class is c3. The most "unconventional" class is c1 (Figure 3), of which cities are much more *isolated* and *centralized* than what are expected of them by the general patterns. The cities in c1 include (Table 7), Yuma, AZ, Albuquerque, NM, Miami, FL, and Odessa, TX. The class partitions are highly distinct (Table 5).

Asians
For Asians, three combination-patterns of residential segregation are identified. The majority of the cities (82.1%) belong to c3, which has the best combination-pattern of the three (Table 3). The "worst" combination-pattern of segregation for Asians is c2 (Figure 4), which includes cities such as Edison, NJ, Houston, TX, Los Angeles, CA, Oakland, CA, Sandusky, OH, Stockton, CA, and Newark, NJ.

Racial Comparisons
On average, the combination-pattern of segregation is the worst for blacks and the best for Asians among three races (Figure 5). However, Asians on average show the highest level of *concentration,* as well as comparably high level of *centralization*. Blacks, on the other hand, are segregated far more strongly than other two races in terms of both dissimilarity and isolation. Hispanics' average pattern of segregation is generally in-between blacks and Asians, but Hispanics are the *least centralized* group of the three.

As expected, each racial group's "best" combination-pattern of segregation is quite alike in their magnitudes and shapes (Figure 7). But, the proportion of cities belonging to the "best" class varies across race. For Asians, 82.1% of the cities fashion the “best” combination-pattern (Table 3), while for blacks only 31.8% (Table 1).

On the other hand, each racial group’s “worst” combination-pattern of segregation is highly distinct (Figure 6). The discrepancy in magnitudes of segregation measures for each segregation domain is highly significant. For example, the cities in the “worst” class for blacks experience nearly double the segregation in evenness and exposure as those of Asians. The “worst” class for Hispanics trails the segregation values of blacks’ “worst” class in all categories by around a third of its segregation values. Asians’ “worst” class, however, shows greater segregation than Hispanics in terms of concentration and centralization.

Finally, there are several combination-patterns of segregation for blacks and Hispanics that are quite unusual in their magnitudes and shapes—in comparison to each race’s general patterns (Figure 8). Table 7 lists some of these cities.

Consequences of Different Combination-Patterns

********THIS WOULD BE A MAJOR PART OF MY ANALYSIS WHEN I FINISH CONSTRUCTING THE DATA (See below for example format of a table)***

Types of Segregation Patterns (Hisp)	Homicide Rates (Not actual)	Mortality	Joblessness	Homicide Victimization
c1	?	?	?	?
c2	?	?	?	?
c3	?	?	?	?
c4	?	?	?	?
c5	?	?	?	?
Overall		**100%**	**100%**	**100%**

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Table 1. Mean segregation index values across latent classes and class membership (Blacks)

	Five Dimensions of Residential Segregation						Class Membership	
Latent Classes	**D**	**xPx**	**ACO**	**ACE**	**SP**		Number of Cities	Pct
c1	0.709	0.690	0.886	0.776	0.858		17	4.5%
c2	0.412	0.423	0.681	0.516	0.667		40	10.5%
c3	0.630	0.516	0.914	0.706	0.747		56	14.7%
c4	0.536	0.322	0.925	0.736	0.662		104	27.4%
c5	0.800	0.769	0.949	0.715	1.000		6	1.6%
c6	0.357	0.066	0.929	0.752	0.602		121	31.8%
c7	0.563	0.592	0.641	0.678	0.769		14	3.7%
c8	0.438	0.129	0.863	0.249	0.617		22	5.8%
Average	0.487	0.302	0.884	0.685	0.671		380	100.0%

Note: SP values are normalized such that the maximum value is 1 based on the highest SP value among the findings, which is 1.69.

Table 2. Mean segregation index values across latent classes and class membership (Hispanics)

	Five Dimensions of Residential Segregation						Class Membership	
Latent Classes	**D**	**xPx**	**ACO**	**ACE**	**SP**		Number of Cities	Pct
c1	0.405	0.721	0.395	0.618	0.680		12	3.2%
c2	0.499	0.469	0.841	0.635	0.705		48	12.6%
c3	0.285	0.062	0.856	0.591	0.600		217	57.1%
c4	0.436	0.224	0.883	0.662	0.635		87	22.9%
c5	0.570	0.579	0.768	0.574	0.825		16	4.2%
Average	0.362	0.193	0.842	0.613	0.633		380	100.0%

Table 3. Average latent class probabilities for most likely latent class membership (Asians)

	Five Dimensions of Residential Segregation						Class Membership	
Latent Classes	**D**	**xPx**	**ACO**	**ACE**	**SP**		Number of Cities	Pct
c1	0.327	0.042	0.910	0.678	0.597		312	82.1%
c2	0.443	0.416	0.863	0.644	0.674		15	3.9%
c3	0.428	0.161	0.943	0.724	0.622		53	13.9%
Average	0.346	0.073	0.913	0.683	0.603		380	100.0%

Table 4. Average latent class probabilities for most likely latent class membership (Blacks)

	c1	c2	c3	c4	c5	c6	c7	c8
c1	0.96	0.00	0.02	0.00	0.01	0.00	0.01	0.00
c2		0.95	0.01	0.04	0.00	0.00	0.01	0.00
c3			0.97	0.02	0.00	0.00	0.00	0.00
c4				0.95	0.00	0.01	0.00	0.01
c5					1.00	0.00	0.00	0.00
c6						0.96	0.00	0.02
c7							0.99	0.00
c8								0.92

Table 5. Average latent class probabilities for most likely latent class membership (Hispanics)

	c1	c2	c3	c4	c5
c1	0.99	0.007	0	0	0
c2	0.003	0.94	0	0.029	0.029
c3	0	0	0.96	0.043	0
c4	0	0.016	0.071	0.91	0
c5	0	0	0	0	1.00

Table 6. Average latent class probabilities for most likely latent class membership (Asians)

	c1	c2	c3
c1	0.99	0.00	0.01
c2	0.00	1.00	0.00
c3	0.07	0.00	0.94

Table 7. The list of cities in the "unconventional" classes of combination-patterns

Cities in C2 for blacks:	Cities in C7 for blacks:	Cities in C8 for blacks:	Cities in C1 for Hispanics:
Anderson, SC	Albany, GA	Barnstable Town, MA	Albuquerque, NM
Athens-Clarke County, GA	Baton Rouge, LA	Bristol, VA	Brownsville-Harlingen, TX
Auburn-Opelika, AL	Columbia, SC	Brownsville-Harlingen, TX	Corpus Christi, TX
Augusta-Richmond County, GA-	Columbus, GA-AL	Cambridge-Newton-Framinghan	El Centro, CA
Brunswick, GA	El Centro, CA	Carson City, NV	Elmira, NY
Burlington, NC	Glens Falls, NY	Cumberland, MD-WV	Hanford-Corcoran, CA
Charleston-North Charleston, SC	Jackson, MS	Essex County, MA Metropolitan	Las Cruces, NM
Charlottesville, VA	Macon, GA	Fort Walton Beach-Crestview-D	McAllen-Edinburg-Pharr, TX
Danville, VA	Memphis, TN-MS-AR	Hickory-Morganton-Lenoir, NC	Merced, CA
Decatur, AL	Montgomery, AL	Holland-Grand Haven, MI	Miami-Miami Beach-Kendall, F
Dothan, AL	Pine Bluff, AR	Honolulu, HI	Odessa, TX
Dover, DE	Richmond, VA	Johnstown, PA	Yuma, AZ
Durham, NC	Spartanburg, SC	Jonesboro, AR	
Elmira, NY	Tuscaloosa, AL	Kingsport-Bristol, TN-VA	
Fayetteville, NC		Kingston, NY	
Florence, SC		Monroe, MI	
Goldsboro, NC		Napa, CA	
Greenville, NC		Ocean City, NJ	
Greenville, SC		Palm Bay-Melbourne-Titusville, FL	
Hanford-Corcoran, CA		Rockingham County-Strafford County, NH Metropolitan Divisio	
Hattiesburg, MS		Salisbury, MD	
Hinesville-Fort Stewart, GA		Sarasota-Bradenton-Venice, FL	
Killeen-Temple-Fort Hood, TX			
Lafayette, LA			
Longview, TX			
Lynchburg, VA			
Myrtle Beach-Conway-North Myrtle Beach, SC			
Raleigh-Cary, NC			
Rocky Mount, NC			
San Diego-Carlsbad-San Marcos, CA			
Sioux Falls, SD			
Springfield, MO			
Sumter, SC			
Tallahassee, FL			
Tyler, TX			
Valdosta, GA			
Vineland-Millville-Bridgeton, NJ			
Virginia Beach-Norfolk-Newport News, VA-NC			
Warner Robins, GA			
Wilmington, NC			

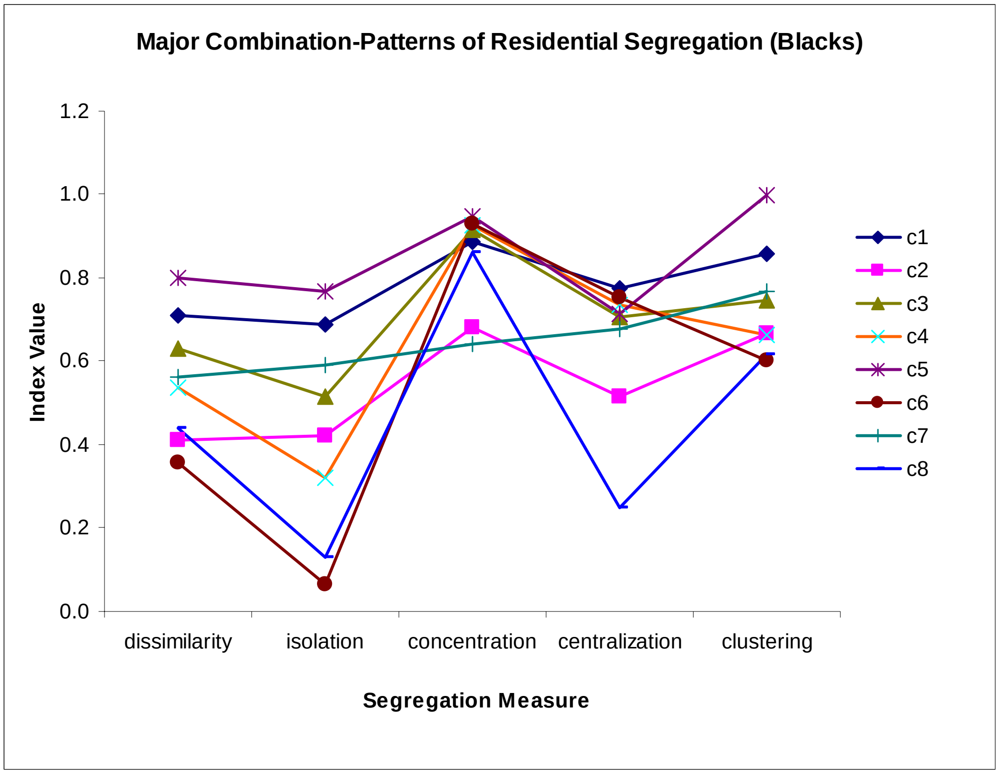

Figure 2. Combination-patterns of residential segregation for blacks

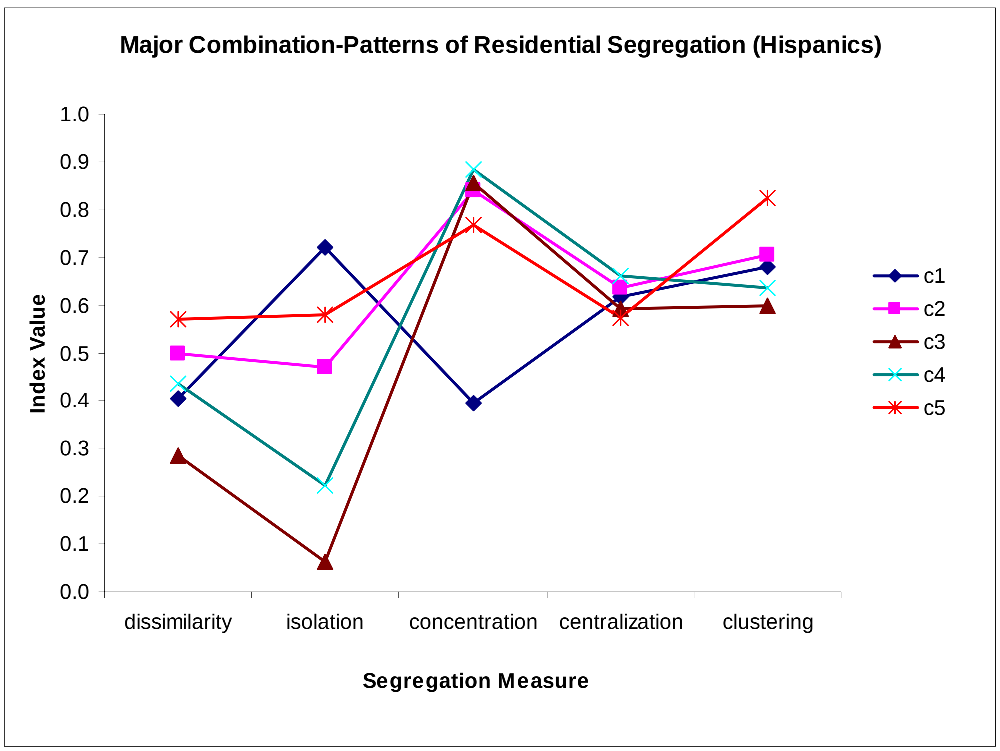

Figure 3. Combination-patterns of residential segregation for Hispanics

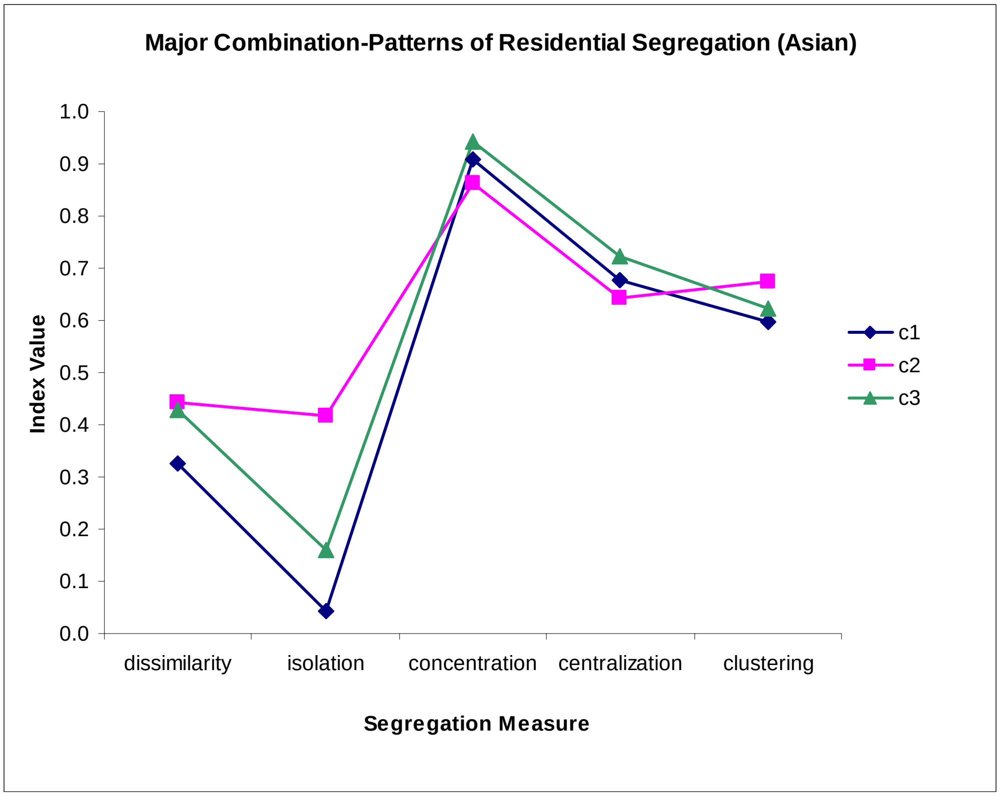

Figure 4. Combination-patterns of residential segregation for Asians

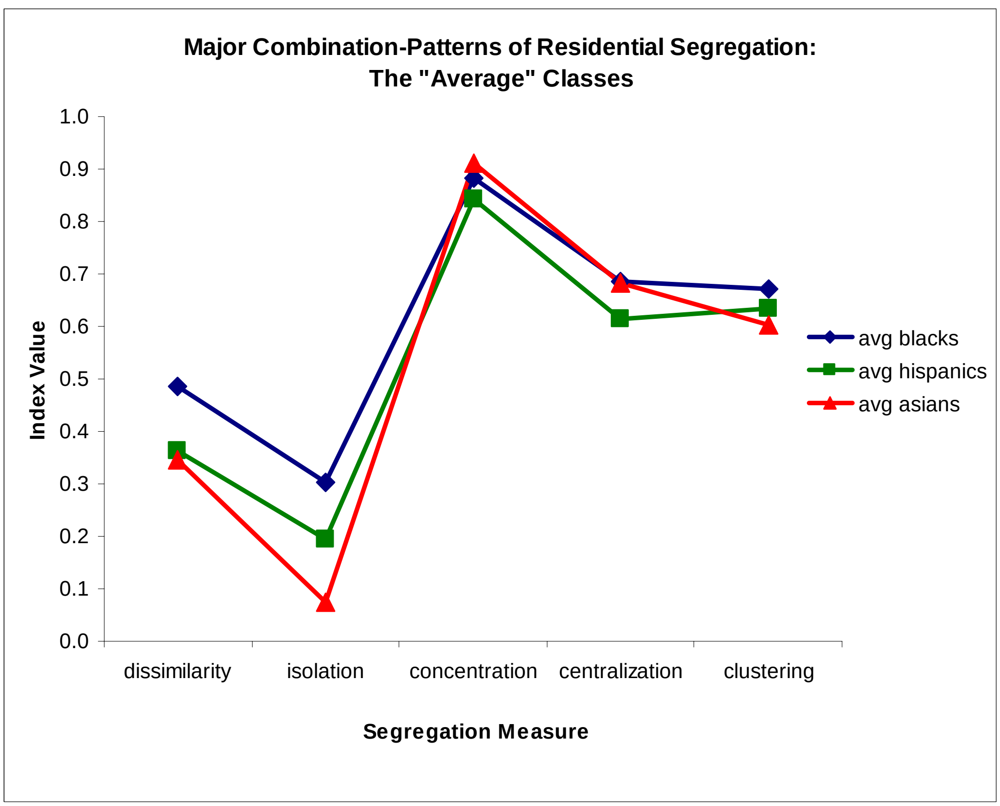

Figure 5. Combination-patterns of residential segregation for the “average” classes

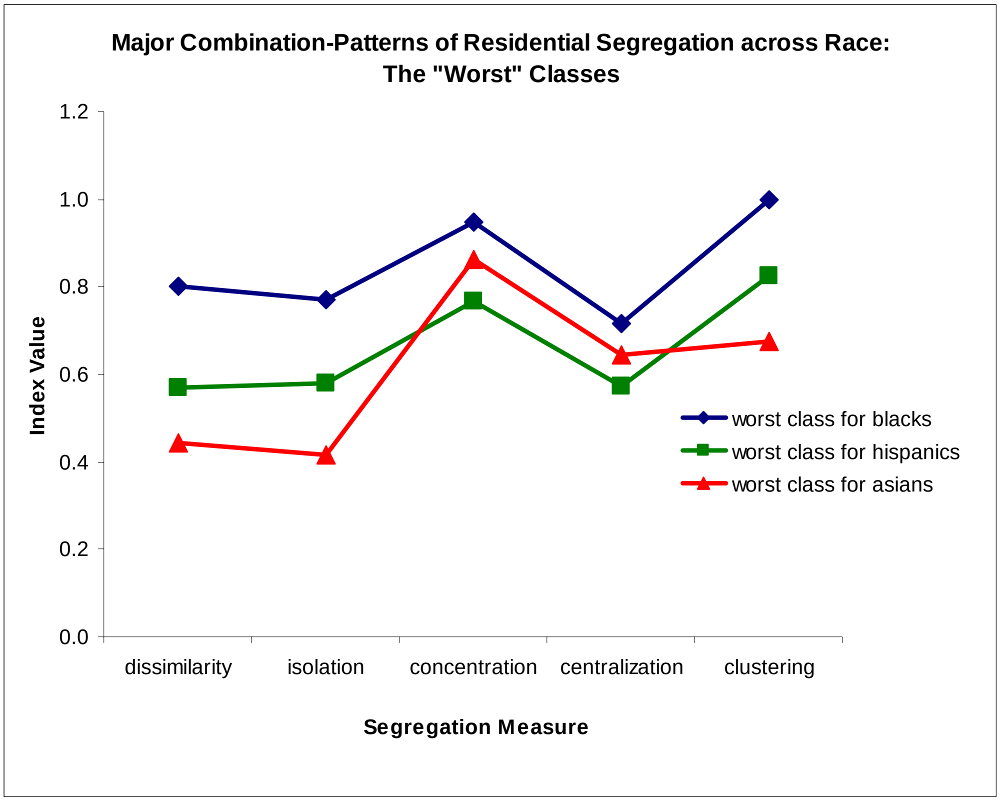

Figure 6. Combination-patterns of residential segregation for the "worst" classes

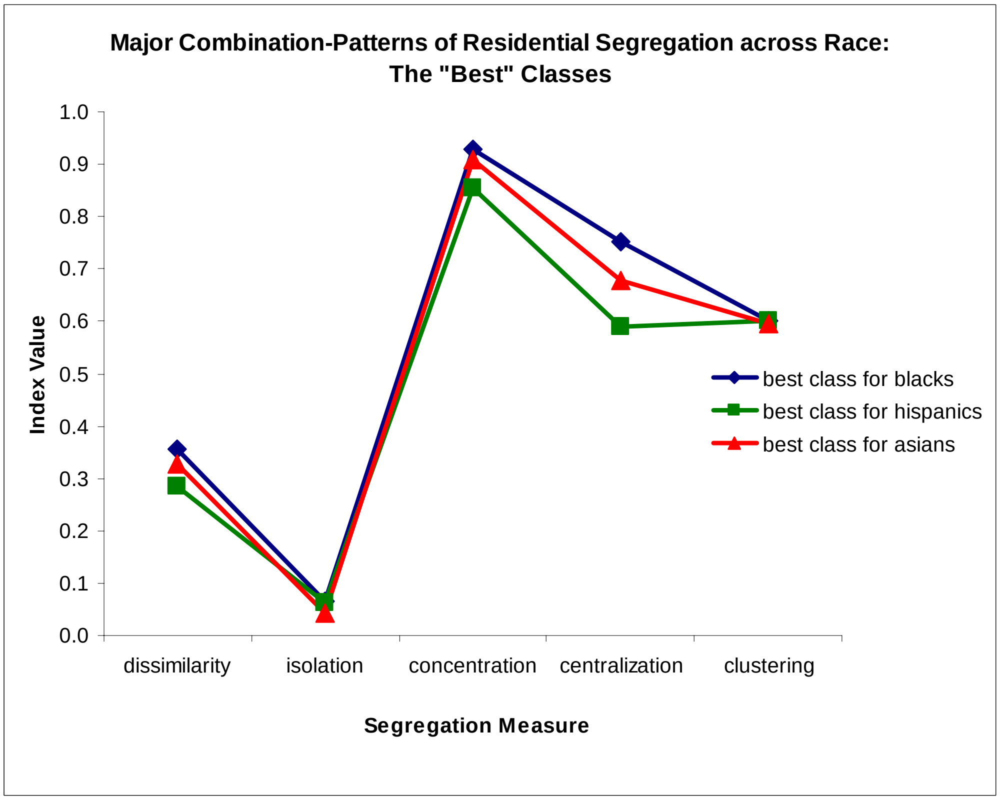

Figure 7. Combination-patterns of residential segregation for the "best" classes

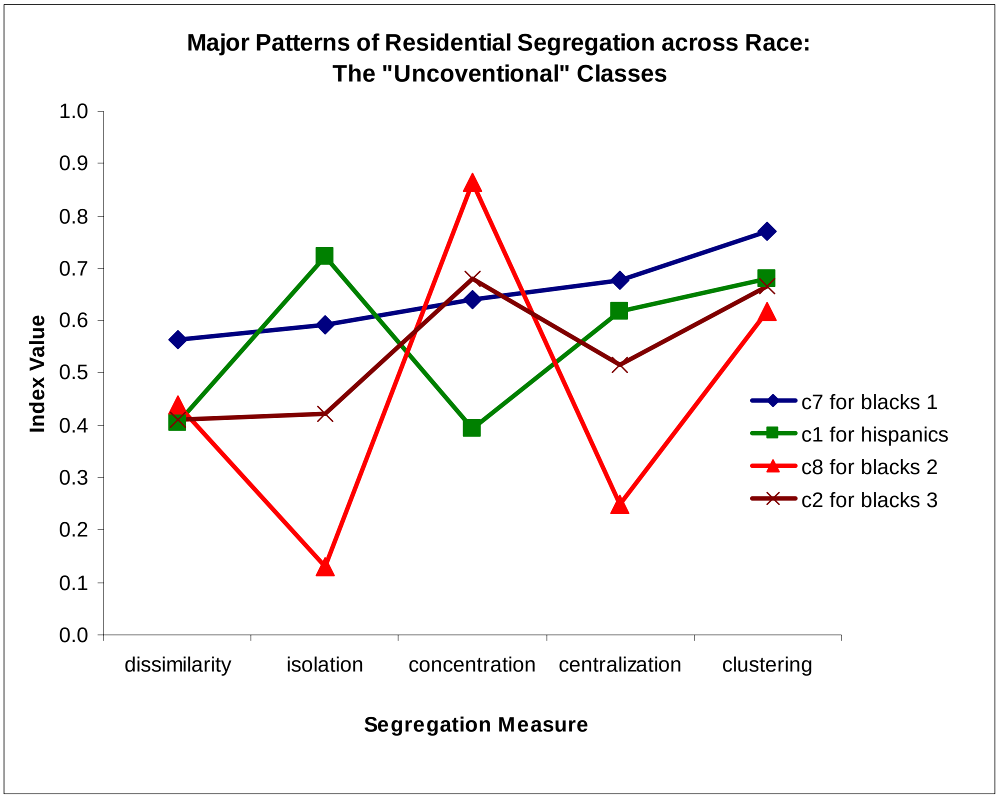

Figure 8. Combination-patterns of residential segregation for the "unconventional" classes

Appendix: Five Dimensions of Residential Segregation

Evenness. Massey and Denton (1988) define evenness as "the differential distribution of two social groups among areal units in a city" (p283). Evenness is "not measured in any absolute sense, but is scaled relative to some other group" and is maximized when "all areal units have the same relative number of minority and majority members as the city as a whole" (p284). Evenness is considered "aspatial" because it does not take into account spatial patterning; for example, the city A and city B could be different in terms of the size and shape of the areal units but could still have same unevenness as long as they have the same distributional properties (cf. see the review by Reardon & O'Sullivan 2004). Massey and Denton (1988) find *the Index of Dissimilarity* to be the best instrument to measure unevenness (see Massey & Denton 1988:284 for the formula). D represents the "proportion of minority members that would have to change their area of residence to achieve an even distribution"—i.e., minority members' moving from overrepresented areas of the city to the underrepresented ones. The index varies between 0 to 1.

Exposure. Massey and Denton (1988) define exposure as "the degree of potential contact, or the possibility of interaction, between minority and majority group members within geographic areas of a city" (p287). Like evenness, exposure is also considered "aspatial" because its variation is impervious to the spatial patterning (cf. see Reardon and O'Sullivan 2004). Unlike exposure, however, exposure is dependent on the population sizes of the groups being compared; thus, even if city A and city B have the same evenness, if city A's relative size of the minority to majority group is smaller than that of city B, then city A will have less exposure than does city B. Massey and Denton find the Index of Interaction (P*) to be the best instrument to measure exposure (see Massey & Denton 1988:288 for the formulat). I use the index of Isolation (xPx), which is simply 1-P*. The index ranges between 0 and 1, and represents the probability that a minority group member, x, is exposed to its own group member, x, by virtue of the minority group's isolation from the majority group, y, living in the same areal unit.

Concentration. Massey and Denton define concentration as the "relative amount of physical space occupied by a minority group in the urban environment" (p289). Unlike evenness and exposure, concentration is a spatial measure because its value pertains directly to the size and shapes of the areal units. Two cities with same evenness and exposure could show different levels of concentration depending on the sizes of the areal units. Massey and Denton's index choice for measuring concentration was the Relative Concentration Index (RCO) (see Massey & Denton 1988:291 for the formula). The index varies between -1 and 1, with the score 0 indicating the equal concentration by the two groups, while -1 indicating maximum possible extent to which the majority group Y's concentration exceeds that of the minority group X and 1 the opposite. The index "measures the share of urban space occupied by group X compared to group Y" (Massey & Denton 1988:291). For this paper, I use absolute concentration index (ACO), which gives the concentration of minority group in a more absolute sense, apart from the distribution of the majority group. I believe the measure of concentration should pertain directly to the size of the land only and the relative concentration of the majority should have minimal meaning, as these are already accounted for by other measures of segregation. ACO varies between 0 and 1, with the score 0 representing the minimum concentration and 1 maximum concentration.

Centralization. Massey and Denton (1988) define centralization as “the degree to which a group is spatially located near the center of an urban area” (p291). Like concentration, centralization is a spatial measure, but unlike concentration centralization pertains to a specific area: center city. Thus, two cities can have same concentration levels but if city A’s concentration is closer to the center of the city than is city B’s, then city A’s centralization would be higher than that of B. Massey and Denton’s choice for measuring concentration was the absolute centralization index (ACE) (see Massey & Denton 1988:293 for the formula). The index ranges from -1 to 1 and represent a likelihood of the minority group member x to live nearer the city center, with 1 indicating 100% chance of living near the city center while -1 indicating 0%. The value 0 indicates no differences in the proportion of the minority residences in areal units all across the metropolitan area.

Clustering. Massey and Denton (1988) define clustering as “the extent to which areal units inhibited by minority members adjoin one another, or cluster, in space” (p293). Like concentration and centralization, clustering is a spatial measure, whose value depends directly on spatial patterning. Unlike concentration or centralization, however, clustering pertains to the aggregate patterns of areal units rather than within-areal unit patterns. Thus, two cities with same concentration and centralization could theoretically have different clustering if the areal units were positioned such that the residences of minority groups were more/less contiguous across tracts. Massey and Denton’s choice for measuring clustering was the Index of Spatial Proximity (SP) (see Massey & Denton 1988:295 for the formula). The index is greater than 1 if members of both the minority and majority live nearer to their own members than to the others while less than 1 if opposite. The value 1 indicates that the level of clustering is same for both groups. For this paper, I normalized SP so as to make the maximum SP the value of 1 based on the highest SP value among the sample’s findings, 1.69.