An analysis of racial-ethnic neighborhood transitions in the U.S. South from 1990-2010

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Abstract

The late 20th century and early 21st century, brought a new wave of immigration to new destinations in the South shifting neighborhood racial-ethnic change. While scholars have looked at these racial-ethnic transitions quantitatively at the national scale and qualitatively at the local level, research on the impacts of this immigration neglects the effect of regional differences on neighborhood change. This paper looks at racial-ethnic transitions from 1990 to 2010 in large metro areas in the U.S. South. I find an over arching pattern of diversification in Southern neighborhoods and an increase in Black integration into neighborhoods. Contrary to prior ideas of racial hierarchy, Asian presence is likely to facilitate Black integration into a neighborhood, while Latinx presence does not. Log-multiplicative analysis reveals that these trends remained similar though less strong from 2000 to 2010.

INTRODUCTION

During the 1990s and 2000s, the U.S. experienced significant shifts in immigration patterns as immigrants settled outside of traditional destination cities – like New York, Chicago, Boston, and San Francisco – in favor of new metropolitan areas in the U.S. South – like Atlanta, Dallas, Charlotte, Orlando, and Raleigh (Singer 2014). While the traditional notion of neighborhood change was one in which residents of color "invaded" previously white neighborhoods resulting in white flight to the suburbs and racial succession (Park and Burgess 1925, Duncan and Duncan 1957), the wave of Latinx and Asian immigrants in the late 20th century complicated this predictable pattern.

While scholars have looked at these racial-ethnic transitions quantitatively at the national scale and qualitatively at the local level, research on the impacts of this 20th century wave of immigration neglects the effect of regional differences on neighborhood change, particularly in new destination cities in the South.

The unique history and contemporary conditions of the South has meant that Southern cities have taken shape in ways not captured by traditional models of urban morphology. The industrialization that had swept the Rust Belt cities in the 19th century bypassed the South and resulted in less centralized cities (Lloyd 2012). In addition, the population boom in the South coincided with the age of automobiles and interstate highway construction resulting in a less dense urban form. Thus, in the early 21st century immigrants arriving into Southern cities were encountering more suburban, more sprawling cities than the traditional gateway cities of San Francisco, New York, Chicago, and Boston or even cities that while experiencing in a dip in immigration in 2000 have re-emerged as gateway cities such as Philadelphia, Baltimore, and Minneapolis (Singer 2014).

In this project, I identify the patterns of racial-ethnic change that have occurred with the influx of Latinx and Asian immigrants to the South from 1990 to 2000 and from 2000 to 2010. I use loglinear analysis to to examine the racial-ethnic neighborhood transitions in Southern metropolitan regions specifically using Xie's (1992) log-multiplicative approach.

DATA, SAMPLE, AND MEASURES

Data

My study relies on tract-level data from the U.S. census in 1990, 2000, and 2010 drawn from Social Explorer which have been recalculated and normalized to the 2010 census tract boundary. Consistent with prior literature, I study four racial-ethnic groups: Latinx and non-Latinx whites, Blacks, and Asians. While the 2000 and 2010 Census allow separate categories for Asian and Pacific Islander, the 1990 Census does not. However, the collapsing of the two should not have a significant effect since both numbers were relatively small in 1990. Due to the very small share of Native Americans/American Indians in my data, I had to exclude Native Americans from my analysis. Also following prior literature, I use tracts as a proxy for studying neighborhoods [1] Before I began my

[1] While the social conception of a neighborhood may not necessarily follow the political boundaries of a census tract, tracts continue to be the most robust measure when studying neighborhoods across time. For more information on the complexity of defining neighborhoods, please read Sperling's 2012 "The Tyranny of Census Geography: Small-Area Data and Neighborhood Statistics" and Clapp and Wang's 2006 "Defining neighborhood boundaries: Are census tracts obsolete?", among others.

analysis I had to make two decisions: (1) which southern metropolitan areas should be included in the study and (2) how to classify neighborhoods within each of these metropolitan regions.

Sampling

This study is interested in how the increase of Latinx and Asian populations in 1990 to new immigrant gateways in the South impacted metropolitan areas that had previously little history of immigration. I experimented with several alternative approaches at the metropolitan level, seeking criteria that would establish a significant presence of either Latinx or Asian populations. I require that that in 2010 at least one immigrant group, Latinx or Asian, was present at or above the regional average. This criterion left me with 45 metropolitan regions and 12,466 census tracts.[2]

Table 1. Average Racial-Ethnic Composition in the South compared to the Sample, 2010

	Regional Avg. *(%)*	Sample Avg. *(%)*
White	59.98	50.20
Black	18.84	18.33
Latinx	15.91	24.82
Asian	2.77	4.28
Native American	0.64	0.37
Other	1.86	2.00
Total	100	100

This selection criteria identifies a set of metropolitan regions that stand out from the regional average in 2010. Latinx are nearly 25% of the aggregate population of the sample areas compared to the regional share of 16%. The share of Asians is nearly double that of the regional share. The selection includes many of the largest Southern metropolises: Atlanta, Charlotte, Dallas, D.C., Houston, Miami, Orlando, Raleigh, Richmond, and Tampa. Texas is particularly well represented with 20 cities due to the high number of Mexican migrants. The list of the full sample can be found in the appendix.

Classification

Secondly, I classify the 12,466 census tracts within these 45 metropolitan areas in terms of the specific combination of groups that are present in them. As in Logan and Zhang (2010) and Alba et al. (1995), I am interested in both the combination of minority groups and also the presence of non-Latinx whites. The neighborhoods can be all white, all Black, all Latinx, or all Asian. They can include any combination of two, three, or all four groups bringing the total neighborhood types to 15.

[2]I removed special use census tracts that were labelled 9800 to 9899. These tracts contained little or no population and represented a relatively large special land use area such as large airports, National Parks, military installations, employment centers, or business/industrial parks. Census tracts coded 9900 to 9998 were also removed since they identified tracts that contained only water area. In addition, I removed census tracts that had a zero total population in 1990, 2000, or 2010.

However, the decision must first be made as to the exact criteria to delineate the conceptual categories (i.e. how white is an "all white" neighborhood) for each neighborhood. I use a percentage criterion that also takes into account the overall racial-ethnic composition of the metropolitan areas in my study. Following Logan and Zhang (2010), I use as a reference point the percentage of each group in the overall population of the 45 metropolises in each year (1990, 2000, and 2010), seen in Table 2. Allowing the reference point to shift over time responds to the rapid growth of Latinx and Asian populations.

Table 2. Average Composition of Sample Metros, 1990-2010

	1990	2000	2010
White	66.07	57.74	50.20
Black	17.14	17.68	18.33
Latinx	14.26	19.39	24.82
Asian	2.04	2.98	4.28

Logan and Zhang (2010) use a 25% criterion to label a racial-ethnic group as "present." However, I decide to adopt a 50% criterion. Due to the smaller presence of Asians in the South compared to the national average, a 50% criterion for Asian more accurately represents a "substantial presence" of Asians. I consider a tract to have a substantial presence of a group if the share of residents in that tract is at least 50% of their share in the aggregate sample population. For example, neighborhoods in 2010, were coded as having a "substantial presence" of Asians if Asians were at least 2.14% of the tract since Asians made up 4.28% of the aggregate population. Using this criteria, I created indicator variables for White, Black, Latinx, and Asian presence.

To clarify how tracts are classified by this criterion, table 3 presents the average racial composition of each category of tract in 1990, 2000, and 2010. The table shows that all-white tracts averaged 88.3% white in 2010, with small shares of Black (2.9%), Latinx (5.3%), and Asian (1.0%) residents. All-Black tracts averaged 87.2% Black, all-Latinx tracts 88.0% Latinx, and one all-Asian tract was 66.6% Asian. At the other extreme, the most diverse type of tract containing all four groups (WBLA) had a much larger share of minority groups than the total region's composition. White residents composed of 41.9% of the population (below the sample's average of 50.20%). The share of Blacks in the most diverse tracts at 25.5% is especially large compared to the 18.3% of the sample total. Latinx at 22.4% were close to the 24.8% of the sample. And Asians were 7.1%, compared to 4.3% of the total. The results in table 3 make as clear as possible how these tracts and neighborhoods have been conceptualized in my study.

We can see that almost no all-Asian tracts existed in the South, except for one in 2010, and no all-minority (BLA) tracts were present in the sample southern metro areas from 1990 to 2010. The table also shows some shifts in the average composition of different types of tracts between 1990 and 2010. These shifts reflect the general decline in the non-Latinx white share of the population and the growth of the Latinx and Asian populations in these metro areas.

Table 3. Average Composition of Tracts by Type using 50% criterion, 1990-2010

	1990					2000					2010				
Type	n	W	B	L	A	n	W	B	L	A	n	W	B	L	A
W	2366	94.3	2.2	2.4	0.5	1952	91.3	2.6	3.7	0.5	1535	88.3	2.9	5.3	1.0
B	693	6.9	91.3	1.4	0.2	743	6.6	89.1	2.2	0.3	737	6.3	87.2	4.0	0.5
L	607	12.9	1.1	85.5	0.3	750	10.6	1.5	87.0	0.3	908	9.0	1.8	88.0	0.5
A	-	-	-	-	-	-	-	-	-	-	1	19.4	4.0	6.5	66.6
WB	1082	72.8	24.8	1.6	0.4	928	69.2	25.2	3.0	0.5	873	63.5	27.2	5.4	1.1
WL	935	72.8	2.6	23.5	0.5	1021	66.6	3.3	27.6	0.5	1126	60.7	3.8	32.6	1.0
WA	2202	89.5	3.6	3.3	3.2	1916	84.2	3.8	4.6	5.2	1554	78.5	4.4	6.5	8.0
BL	277	11.4	52.9	35.0	0.3	455	11.0	47.4	39.2	0.5	669	10.1	44.2	43.3	0.8
BA	160	21.2	42.0	32.2	4.0	350	17.7	36.9	35.4	7.0	471	15.0	33.3	41.4	8.0
LA	88	21.8	3.3	71.6	2.9	126	19.1	3.8	71.4	4.3	144	16.0	4.5	72.5	5.9
WBL	291	56.4	23.0	19.5	0.4	461	52.6	21.1	23.4	0.5	645	46.7	21.6	28.2	1.1
WBA	1385	71.8	21.3	3.0	3.5	1280	65.0	22.7	4.6	4.9	1256	58.7	23.3	7.2	7.5
WLA	1408	73.9	4.3	18.2	3.2	1186	64.1	4.7	23.8	5.0	1033	58.1	5.4	27.6	6.5
WBLA	972	53.4	25.5	15.9	4.7	1298	44.9	27.5	18.5	5.9	1514	41.9	25.5	22.4	7.1

ANALYSIS

In my analysis of neighborhoods, I am particularly interested in several patterns hypothesized in past literature: (1) white exodus from minority groups generally, (2) white exodus from Black residents, (3) Latinx and Asian facilitation of Black entry, and (4) establishment of "Global Neighborhoods." The table in Appendix B shows the the most common outcomes in 2000 and 2010 for W, WB, WA, WL, WLA, WBA, WBL, and WBLA. While Logan and Zhang (2010) found WBLA tracts to have the highest degree of stability compared to all other types when looking at tracts at the national level, Southern tracts that were WBLA in 1990 did not show the same amount of stability. In fact, few tracts transitioned to WBLA from 1990 to 2000. Those that transitioned to WBLA had either a substantial presence of *both* Latinx and Asians or of Asians and Blacks. Surprisingly, Latinx presence seemed to be less of a requirement for neighborhoods to become global. In fact, for neighborhoods that maintained a "global" status in 1990 and 2000, 20% experienced a loss of both white and Latinx presence with Blacks and Asians remaining.

Another observation is the prevalence of certain specific sequences of change. White tracts in 1990 - if they do not remain all white - are most likely to become white and Asian. This trend continues into the following decade, and we continue to see how a substantial number of Asians can facilitate Black entry into white neighborhoods: WBA neighborhoods are the third most likely outcome from WA tracts after majority white. This pattern is also seen when the tract is categorized as white and Asian in 1990. The following trajectories also show evidence of Asian presence facilitating Black entry into neighborhoods. There is less evidence of white exodus when they gain a minority presence except for WBL neighborhoods in 1990. 16% of these tracts became BL in 2000 and 77.6% remained BL in 2010.

To further investigate neighborhood transitions across time, I replicate Xie's (1992) log-linear analysis approach to my neighborhood transition matrices. The full typology matrix creates an un-

Table 4. Transition Matrices for Neighborhood Type, 1990 - 2000 and 2000-2010

1990-2000 (Transition = 1)

Neighborhood Type	W	B	WB	WL +WA	BL +BA	L+A +LA	WBL +WBA	WLA	WBLA	**Total**
W	1540	0	96	582	0	0	91	48	9	**2366**
B	0	584	7	0	59	0	1	0	42	**693**
WB	104	33	625	52	14	0	225	2	27	**1082**
WL+WA	266	0	55	1913	4	65	371	338	125	**3,137**
BL+BA	0	19	0	1	365	34	10	0	8	**437**
L+A+LA	0	0	0	6	7	674	0	8	0	**694**
WBL+WBA	14	54	141	84	93	6	913	13	358	**1,676**
WLA	27	0	0	281	14	82	44	736	224	**1408**
WBLA	1	53	4	18	249	15	86	41	505	**981**
Total	**1952**	**743**	**928**	**2937**	**805**	**876**	**1741**	**1186**	**1298**	**12466**

2000-2010 (Transition = 2)

Neighborhood Type	W	B	WB	WL +WA	BL +BA	L+A +LA	WBL +WBA	WLA	WBLA	**Total**
W	1193	0	94	461	0	0	107	60	37	**1952**
B	0	598	25	1	64	0	20	0	35	**743**
WB	81	23	575	16	7	0	195	3	28	**928**
WL+WA	240	0	30	1815	10	65	318	296	163	**2937**
BL+BA	0	15	6	3	652	54	28	3	44	**805**
L+A+LA	0	0	0	21	21	826	0	6	2	**876**
WBL+WBA	12	24	136	117	101	9	1017	24	301	**1741**
WLA	6	0	0	214	17	77	42	596	234	**1186**
WBLA	3	77	7	32	268	22	174	45	670	**1298**
Total	**1535**	**737**	**873**	**2680**	**1140**	**1053**	**1901**	**1033**	**1514**	**12466**

wieldy 14 × 14 table, which can be found in Appendix C. I collapsed the categories resulting in 9 types of neighborhoods: only white (W), only Black (B), white and Black only (WB), White and single immigrant group (WL,WA), Black and single immigrant group (BL, BA), only immigrant (L,A,LA), semi-global (WBL,WBA), white and both immigrant groups (WLA), and global neighborhood (WBLA). Table 4 shows the 9 × 9 transition matrices for the first ten-year transition 1990 to 2000, and the second ten-year transition 2000 to 2010.

While most neighborhoods remain the same neighborhood type as evidenced by clustering along the matrix diagonal, there is also evidence of movement between different types of neighborhoods. Unsurprisingly, when we look at the marginal totals we see an increase of neighborhood types that include at least one immigrant group as we transition from 1990 to 2000 to 2010. Only white and only Black neighborhoods decrease. The most prevalent type of neighborhood in the South were neighborhoods that had both white and one immigrant group; however, these neighborhoods decreased slightly in number as semi-global and global neighborhoods increased. There is also an increase of neighborhoods that are Black and one immigrant group only.

Models for Analyzing Southern Neighborhood Transitions

I apply various log-linear models to explicitly test neighborhood transition patterns within each time period and across time periods. Below I outline the 15 models that I test:

Model 1: The null association model, *NA*, is the baseline model. As a conditional independence model, it assumes that there is a null association between neighborhood type in time one and neighborhood type in time two given the transition time period. It takes the following log-additive form:

$$\log F_{ijk} = \lambda + \lambda_i^R + \lambda_j^C + \lambda_t^L + \lambda_{ik}^{RL} + \lambda_{jk}^{CL} + Q_{ijk}^{RCL} \quad (1)$$

where R, C, and L denote the neighborhood type at time one, neighborhood type at time two, and time period variables respectively. $i = 1, ...I, j = 1, ...J, \text{and} k = 1, ...K$. Q_{ijt} is the quasi-independence design matrix for the diagonal cells. My analysis is restricted to off-diagonal cells since two-way associations can be dominated by diagonal cells representing neighborhoods that do not change. While excluding diagonal cells necessarily precludes a comparative analysis between neighborhoods that remained the same type, that is not the focus of my paper. The *NA* model contains only the two-way interactions between RL and CL. My following models focus on the specification of the the two-way interaction between RC and the three-way interaction between RCL.

Following Xie (1992), five model specifications (*R*, *C*, *R*+ *C*, *RC*, and *FI*) are used to describe the two-way associations. Each specification (except *RC)* is modified by three subscripts: o stands for homogeneity across time periods; u stands for uniform comparison across time periods under the uniform layer effect model; and x stands for log-multiplicative across time periods using the log-multiplicative layer effect model. The uniform layer effect model specifies that the three way interaction be modelled by $\exp(\beta_k ij)$, where i and j are interval variables and β_k is the time period specific parameter describing the strength of the R and C association for the kth time period.

The log-multiplicative layer allows the R and C association to vary log-multiplicatively with time period. That is, the log-multiplicative layer effect model specifies the RC two-way and RCL three-way interactions as the log-multiplicative product of two things: the overall RC two-way association and a deviation parameter for the kth time period. I am particularly interested in the log-multiplicative models as they are invariant under switches in the categories of the row or column variables. Among other things, this means that relative distances (and orderings) between row scores and between column scores are unchanged when categories are switched (Clogg 1982).

My first specification is the row effect model (R).

$$R_o\text{: } \log F_{ijk} = NA \text{ model} + j\mu_i \quad (2)$$

$$R_u\text{: } \log F_{ijk} = NA \text{ model} + j\mu_i + \beta_k ij \quad (3)$$

$$R_x\text{: } \log F_{ijk} = NA \text{ model} + \beta_k i\mu_i \quad (4)$$

where μ_i is the row score. This model requires correct ordering and equal distances of the neighborhood types in time two (the column variable).

The second specification, the column effect model (C), is similar to the row effect model; however, the model uses a column score, ν_j , and requires correct ordering and equal distances of the neighborhood types in time one (the row variable) rather than in time two.

$$C_o\text{: } \log F_{ijk} = NA \text{ model} + i\nu_j \tag{5}$$

$$C_u\text{: } \log F_{ijk} = NA \text{ model} + i\nu_j + \beta_k ij \tag{6}$$

$$C_x\text{: } \log F_{ijk} = NA \text{ model} + \beta_k j\mu_i \tag{7}$$

The third specification, row and column effects model I ($R + C$), uses both row and column scores and requires the correct ordering of both time one and time two neighborhood types.

$$(R + C)_o\text{: } \log F_{ijk} = NA \text{ model} + j\mu_i + i\nu_j \tag{8}$$

$$(R + C)_u\text{: } \log F_{ijk} = NA \text{ model} + j\mu_i + i\nu_j + \beta_k ij \tag{9}$$

$$(R + C)_x\text{: } \log F_{ijk} = NA \text{ model} + \beta_k(j\mu_i + i\nu_j) \tag{10}$$

The $(R + C)_u$ model was favored by Yamaguchi (1987); however, it operates under the assumption that the variables have a monotonic scale. Since my neighborhood type variables measure racial-ethnic composition, there is no explicit ordering of the categories. Thus, I do not expect any of the models that require correct ordering to have a good fit.

The fourth specification, row and column effects model II (RC) does not require the correct ordering of time one or time two neighborhood types. The log-multiplicative RC II model (RC_x) assumes that the categories are ordinal but not necessarily correctly ordered. As Xie (1992) notes this model has been used in various forms by scholars, such as Clogg (1982) and Goodman (1986).

$$(RC)_o\text{: } \log F_{ijk} = NA \text{ model} + \mu_i\nu_j \tag{11}$$

$$(RC)_x\text{: } \log F_{ijk} = NA \text{ model} + \beta_k\mu_i\nu_j \tag{12}$$

The full two-way interaction model (FI) places no restrictions on the interaction between the neighborhood types at time one (R) and time two (C).

$$FI_o\text{: } \log F_{ijk} = NA \text{ model} + \lambda_{ij}^{RC} \tag{13}$$

$$FI_u\text{: } \log F_{ijk} = NA \text{ model} + \lambda_{ij}^{RC} + \beta_k ij \tag{14}$$

$$FI_x\text{: } \log F_{ijk} = NA \text{ model} + \psi_{ij}\phi_k \tag{15}$$

Parameters ψ_{ij} and ϕ_k are latent scales of my variables: ψ_{ij} represents the association between neighborhood type in time one and neighborhood type in time two, whereas ϕ_k represents the association levels for time one compared to time two. In other words, to create a more parsimonious model, I allow flexible specification for the typical association pattern between R and C and constrain its cross-layer variation to be log-multiplicative. The log-multiplicative layer effect model builds on the assumption that the neighborhood transitions are common for both time periods, but that the level of the association differs between time periods.

RESULTS

Table 5 displays the results of various models applied to my neighborhood transition data. The goodness-of-fit of each model is assessed using the log-likelihood ratio chi-squared statistic, L^2 along with its degrees of freedom and p-value and by the BIC statistic. When BIC is negative, the null hypothesis is preferred relative to the saturated model; in other words, the presented model obtains similar expected frequencies to the saturated model, but is more parsimonious. In the presence of a large amount of informative data, even 'good' models are typically rejected by conventional lack-of-fit tests based on statistical significance, so I also include the dissimilarity index, Δ, which ranges from 0 (perfect fit) to 1 (Kuha and Firth 2009). The dissimilarity index aims to quantify lack of model fit by estimating the smallest fraction of the population under study that would need to be re-classified in order to make the fitted model exactly correct. A value less than or equal to 0.02 is considered a good model.

Table 5. Goodness-of-fit of Models on Neighborhood Racial-Ethnic Transitions in the South

Model	(Equation) Description	L^2	*df*	p	BIC	Δ
NA	(1) Null Association between R and C given L	8590	110	.000	7477	.147
R_o	(2) homogeneous row effect association	7463	102	.000	6430	.126
R_u	(3) uniform row effect association	7463	101	.000	6440	.126
R_x	(4) log-multiplicative row effect association	7456	101	.000	6434	.126
C_o	(5) homogeneous column effect association	5602	102	.000	4569	.097
C_u	(6) uniform column effect association	5601	101	.000	4579	.097
C_x	(7) log-multiplicative column effect association	5595	101	.000	4573	.097
$(R+C)_o$	(8) homogeneous row and column effect association I	4987	94	.000	4036	.084
$(R+C)_u$	(9) uniform row and column effect association I	4987	93	.000	4046	.084
$(R+C)_x$	(10) log-multiplicative row and column effect association I	4966	92	.000	4035	.084
RC_o	(11) homogeneous row and column effect association II	3154	95	.000	2192	.064
RC_x	(12) log-multiplicative row and column effect association II	3118	94	.000	2166	.062
FI_o	(13) homogeneous full two-way R and C interaction	167	55	.000	-389	.015
FI_u	(14) uniform full two-way R and C interaction	167	54	.000	-380	.015
FI_x	(15) log-multiplicative layer effect model	142	54	.000	-404	.013

By the log-likelihood ratio test, all the models do not fit the data satisfactorily. Part of the reason for this is the large sample size (12,466). According to the BIC statistic, only the FI models are preferred to the saturated model; the BIC for all other models remains positive. While a chi-square test cannot be used to compare u- and x-specified models since they are not nested, a BIC statistic may be used. Similar to Xie (1992), the x-model yields smaller BIC statistics than does the corresponding u-model for all but one model (R). Still the differences for the log-likelihood statistics between all the u- and x-specified models are fairly small except for the RC and FI models. The delta statistic does not change for the R, C, and $(R+C)$ models.

Model FI_o leaves the time one and time two neighborhood type association free but restricts it to be the same across two time periods. It reduces L^2 to 167 from model NA for 55 degrees of freedom and the BIC becomes negative (-389) indicating a good fit. Allowing the association to vary log-multiplicatively across the two time periods, model FI_x further improves the goodness-of-fit with a L^2 of 142 and a BIC of -404. By both statistics, I conclude that the FI_x model is the preferred model of those tested. The Δ statistic of .013 confirms the goodness of fit. Only 1.3% of the census tracts would need to be reclassified in order to make the fitted model perfectly correct. While the full two-way interaction models use substantially more degrees of freedom than the RC models, the fit of the models are substantially better. The interpretation of this model follows my expectation: While the associations are different between different neighborhood types within a time period, these associations are the same when compared across time periods. However, the magnitude of the associations do vary from 1990 to 2010 and are not homogeneous. My model sets the ϕ_1 of transition one (1990-2000) at 1.00, and found the ϕ_2 of transition two (2000-2010) to be 0.854. From the formula to find the conditional log-odds for the kth time period:

$$\log(\theta_{ijk}) = \log(\theta_{ij})\phi_k \tag{16}$$

we can derive the relative magnitude of the differences between time periods:

$$\frac{\log(\theta_{ij|2}) - \log(\theta_{ij|1})}{\log(\theta_{ij|1})} = \frac{\log(\theta_{ij})(\phi_2 - \phi_1)}{\log(\theta_{ij})\phi_1} = \frac{\phi_2 - \phi_1}{\phi_1} \tag{17}$$

Using the formula and the estimated ϕ parameters from model FI_x, the association between neighborhood types is 14.6 percent less in the later transition from 2000 to 2010 than the initial transition from 1990 to 2000. The full LEM input and output for my FI_x model is found in Appendix D and uses effect coding scheme. Since there are negative coefficients for my variables, the ordering of my variables is not monotonic.

Table 6. Diagonal Odds Ratios

	Odds Ratios
White only	1.11
Black only	1.77
White & Black only	1.71
White & one immigrant group	1.49
Black & one immigrant group	1.38
Immigrant only	1.04
Semi-global	1.31
White & both immigrant groups	1.19
Global	0.98

In looking at the patterns of diagonal ratios as detailed in table 6, there is no strong evidence of "status disinheritance" across time periods. No neighborhood type had ratios under 1.0 except for global neighborhoods. However, even the ratio for global neighborhoods is only slightly under 1.0.

DISCUSSION

The influx of Latinx and Asians to new destinations in the South brought with it changing racial-ethnic composition of neighborhoods. The interaction between Black and Asian populations is especially prevalent. Contrary to prior literature which has noted that Asians may follow white patterns of residence (i.e. following a neighborhood hierarchy with whites as most desireable, Latinx in the middle, and Black neighborhoods as least desireable), my analysis shows that Asian and Black presence together was a common trend among neighborhoods and Asian presence facilitated the entry of Blacks into neighborhoods that were either previoiusly all white or white and immigrant. There is less evidence for this trend for Latinx. In fact, for neighborhoods that maintained a "global" status in 1990 and 2000, 20% experienced a loss of both white and Latinx presence with Blacks and Asians remaining. While this effect might be due to the smaller percentage of Asians in the South overall, my 50% criterion instead of 25% criterion was to ensure that the presence of Asians was substantial. This criterion might mask Latinx patterns, however, since the large percentage of Latinx in Texas might skew the overall proportion making it harder for other metro-area tracts to reach the standard for substantial presence of Latinx. Further research needs to be done to disaggregate the Asian population - is there a difference among which Asian ethnic group is facilitating Black integration?

By running the Xie's (1992) log-multiplicative model. My study also shows that the associations and changes resulting from this influx of immigrants to the South were not isolated to the initial 10 years after 1990. While smaller in magnitude, the associations were still present and from 2000 to 2010. Even though further analysis will be needed once the 2020 census is published to understand the stability (or instability) of these trends, my study preliminarily shows that these neighborhood patterns are not just a fleeting reaction to immigration and will continue to have importance in terms of how racial groups will interact with one another in the South.

Scholars have long understood that urban space can sustain social inequities (Henri Lefebvre 1972, Michel Foucault 1975, David Harvey 2008). Thus, as more people migrate to the South, there has become an increased need and increased lack of literature on how spatial, economic, and built differences in the South effect racial-ethno changes in neighborhoods, and the potential for spacial inequity to be exacerbated or lessened. I call for more urban sociology to look at non-traditional cities. New and rich social patterns are emerging in regions like the South that have a history of being understudied, and it would be irresponsible for social scientists to disregard the South solely because canonical sociology has done so.

I hope to extend my research further and look at predictors of neighborhood transitions. I will run multinomial logistic regressions to analyze changes between the full period of 1990 to 2010. I am interested particularly on several pathways: (1) white only neighborhoods that either stayed white only, allowed black entry (in combination with other minorities), or only allowed immigrant entry, (2) white and immigrant neighborhoods that held on to their status, had white exodus, or had black entry, (3) semi-global neighborhoods that remained the same status or had white exodus, and (4) global neighborhoods that remained global or had white exodus. I hope that further understanding these racial-ethnic changes will allow fields such as city-planning and urban development to enact more equitable policies and projects.

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TABLES AND FIGURES

Appendix A. All Metropolitan Statistical Areas in Sample

STATE	CBSA ID	METRO NAME
Arkansas	22900	Fort Smith, AR-OK
Florida	15980	Cape Coral-Fort Myers, FL
	18880	Crestview-Fort Walton Beach-Destin, FL
	23540	Gainesville, FL
	27260	Jacksonville, FL
	29460	Lakeland-Winter Haven, FL
	33100	Miami-Fort Lauderdale-Pompano Beach, FL
	34940	Naples-Marco Island, FL
	36740	Orlando-Kissimmee-Sanford, FL
	45300	Tampa-St. Petersburg-Clearwater, FL
Georgia	12020	Athens-Clarke County, GA
	12060	Atlanta-Sandy Springs-Marietta, GA
	19140	Dalton, GA
	23580	Gainesville, GA
Maryland	12580	Baltimore-Towson, MD
North Carolina	16740	Charlotte-Gastonia-Rock Hill, NC-SC
	20500	Durham-Chapel Hill, NC
	24660	Greensboro-High Point, NC
	39580	Raleigh-Cary, NC
Oklahoma	36420	Oklahoma City, OK
Texas	10180	Abilene, TX
	11100	Amarillo, TX
	12420	Austin-Round Rock-San Marcos, TX
	15180	Brownsville-Harlingen, TX
	17780	College Station-Bryan, TX
	18580	Corpus Christi, TX
	19100	Dallas-Fort Worth-Arlington, TX
	21340	El Paso, TX
	26420	Houston-Sugar Land-Baytown, TX
	28660	Killeen-Temple-Fort Hood, TX
	29700	Laredo, TX
	31180	Lubbock, TX
	32580	McAllen-Edinburg-Mission, TX
	33260	Midland, TX
	36220	Odessa, TX
	41660	San Angelo, TX
	41700	San Antonio-New Braunfels, TX
	46340	Tyler, TX
	47020	Victoria, TX
	47380	Waco, TX
Virginia	13980	Blacksburg-Christiansburg-Radford, VA
	16820	Charlottesville, VA
	40060	Richmond, VA
	47260	Virginia Beach-Norfolk-Newport News, VA-NC
Washington, D.C.	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV

Appendix B. Neighborhood Pathways for W, WLA, and WB from 1990 to 2010

	1990		2000			2010		
	Type	**No.**	**Type**	**No.**	**%**	**Type**	**No.**	**%**
All White	W	2366	W	1540	65.1	W	1031	66.9
						WA	167	10.8
			WA	413	17.5	WA	163	39.5
						W	112	27.1
						WBA	42	10.2
Both White & Black	WB	1082	WB	625	57.8	WB	435	69.6
						W	64	10.4
			WBA	149	13.8	WBA	58	38.9
						WB	47	31.5
White & Immigrant	WA	2202	WA	1258	57.1	WA	819	65.1
						WBA	165	13.1
			WBA	300	13.6	WBA	180	60.0
						WBLA	70	23.3
			W	228	10.4	W	72	31.6
						WA	86	37.7
	WL	935	WL	582	62.2	WL	427	73.4
			WLA	136	14.5	WLA	47	34.6
						WL	47	34.6
						WBLA	16	11.8
	WLA	1408	WLA	736	52.3	WLA	410	55.7
						WBLA	128	17.4
						WL	77	10.5
			WBLA	224	15.9	WBLA	136	60.7
						BA	35	15.6
			WL	179	12.7	WL	85	47.5
						WLA	48	26.8
			WA	102	7.2	WA	67	65.7
						WLA	24	23.5
Semi-Global	WBA	1385	WBA	729	52.6	WBA	448	61.5
						WBLA	147	20.2
			WBLA	330	23.8	WBLA	187	56.7
						BA	54	16.4
			WB	138	10.0	WB	67	48.6
						WBA	40	29.0
	WBL	291	WBL	151	51.9	WBL	96	63.6
						WL	22	14.6
						BL	16	10.6
			BL	49	16.8	BL	38	77.6
						WBL	6	12.2
			WL	31	10.7	WL	17	54.8
						WBL	6	19.4
						WLA	6	19.4
Global	WBLA	972	WBLA	505	52.0	WBLA	241	47.7
						BA	103	20.4

Appendix C. Full Neighborhood Transition Matrices for Two Time Periods

1990-2000 (Transition = 1)

	W	B	L	WB	WL	WA	BL	BA	LA	WBL	WBA	WLA	WBLA	**Total**
W	1540	0	0	96	169	413	0	0	0	27	64	48	9	2374
B	0	584	0	7	0	0	50	9	0	0	1	0	42	695
L	0	0	580	0	5	0	5	0	9	0	0	8	0	611
WB	104	33	0	625	4	48	12	2	0	76	149	2	27	1088
WL	38	0	57	2	582	36	2	2	8	54	1	136	17	947
WA	228	0	0	53	37	1258	0	0	0	16	300	202	108	2210
BL	0	14	15	0	0	0	221	14	1	8	1	0	3	279
BA	0	5	2	0	0	1	54	76	16	1	0	0	5	160
LA	0	0	54	0	1	0	0	2	31	0	0	0	0	89
WBL	4	5	5	3	31	2	49	4	1	151	4	4	28	294
WBA	10	49	0	138	0	51	7	33	0	29	729	9	330	1394
WLA	27	0	30	0	179	102	0	14	52	35	9	736	224	1418
WBLA	1	53	7	4	13	5	55	194	8	64	22	41	505	981
Total	**1952**	**743**	**750**	**928**	1025	1926	457	352	126	467	1286	1193	1307	12466

2000-2010 (Transition = 2)

	W	B	L	A	WB	WL	WA	BL	BA	LA	WBL	WBA	WLA	WBLA	**Total**
W	1193	0	0	0	94	183	278	0	0	0	37	70	60	37	1962
B	0	598	0	0	25	0	1	63	1	0	2	18	0	35	745
L	0	0	700	0	0	19	0	12	1	15	0	0	3	0	755
WB	81	23	0	0	575	5	11	6	1	0	72	123	3	28	934
WL	30	0	63	0	0	645	15	7	1	2	68	2	135	53	1025
WA	210	0	0	0	30	42	1113	0	2	0	13	235	161	110	1926
BL	0	10	31	0	5	2	1	350	13	2	18	5	2	16	457
BA	0	5	10	0	1	0	0	90	199	11	3	2	1	28	352
LA	0	0	55	0	0	2	0	5	3	56	0	0	3	2	126
WBL	2	1	7	0	11	54	0	58	9	0	243	5	19	52	467
WBA	10	23	1	1	125	2	61	11	23	0	39	730	5	249	1286
WLA	6	0	33	0	0	158	56	9	8	44	36	6	596	234	1193
WBLA	3	77	8	0	7	14	18	58	210	14	114	60	45	670	1307
Total	1548	740	916	1	875	1131	1559	674	472	147	648	1259	1036	1522	12466

Source: 1990, 2000, and 2010 U.S. Census Data drawn from Social Explorer.
Note: W is non-Latinx whites, B is non-Latinx Blacks, L is Latinx, and A is Asian. In transition 1, no neighborhoods were all-Asian or all-minority (BLA). In transition 2, no neighborhoods were all-minority.

Appendix D. LEM input and output for FI_x model

```
*** INPUT ***
*FIx
*Y = year transition, S=start Type, E=end Type
man 3
dim 2 9 9
lab Y S E
mod {YS,YE,spe(SE,5a,Y,c,1),spe(SE,1a,Y,b)}
des [0 1]
dat[
1540 0   96  582  0   0   91   48  9
0    584 7   0    59  0   1    0   42
104  33  625 52   14  0   225  2   27
266  0   55  1913 4   65  371  338 125
0    19  0   1    365 34  10   0   8
0    0   0   6    7   674 0    8   0
14   54  141 84   93  6   913  13  358
27   0   0   281  14  82  44   736 225
1    53  4   18   249 15  86   41  505
1193 0   94  461  0   0   107  60  37
0    598 25  1    64  0   20   0   35
81   23  575 16   7   0   195  3   28
240  0   30  1815 10  65  318  296 163
0    15  6   3    652 54  28   3   44
0    0   0   21   21  826 0    6   2
12   24  136 117  101 9   1017 24  301
6    0   0   214  17  77  42   596 234
3    77  7   32   268 22  174  45  670]

*** STATISTICS ***
Number of iterations = 5000
Converge criterion = 0.0004155918
X-squared = 131.6271 (0.0000)
L-squared = 142.1987 (0.0000)
Cressie-Read = 133.8782 (0.0000)
Dissimilarity index = 0.0132
Degrees of freedom = 54
Log-likelihood = -97102.97905
Number of parameters = 107 (+1)
Sample size = 24933.0
BIC(L-squared) = -404.4944
AIC(L-squared) = 34.1987
BIC(log-likelihood) = 195289.2205
AIC(log-likelihood) = 194419.9581
WARNING: no information is provided on identification of parameters
*** FREQUENCIES ***
Y S E   observed  estimated   std. res.
1 1 1   1540.000  1539.661    0.009
```

1	1	2	0.000	0.008	-0.090
1	1	3	96.000	95.208	0.081
1	1	4	582.000	576.581	0.226
1	1	5	0.000	0.026	-0.162
1	1	6	0.000	0.052	-0.229
1	1	7	91.000	87.754	0.347
1	1	8	48.000	49.493	-0.212
1	1	9	9.000	17.165	-1.971
1	2	1	0.000	0.082	-0.286
1	2	2	584.000	583.953	0.002
1	2	3	7.000	12.908	-1.644
1	2	4	0.000	0.186	-0.432
1	2	5	59.000	58.249	0.098
1	2	6	0.000	0.003	-0.055
1	2	7	1.000	6.815	-2.228
1	2	8	0.000	0.039	-0.197
1	2	9	42.000	30.718	2.035
1	3	1	104.000	107.489	-0.336
1	3	2	33.000	35.400	-0.403
1	3	3	625.000	624.857	0.006
1	3	4	52.000	38.217	2.230
1	3	5	14.000	11.115	0.865
1	3	6	0.000	0.031	-0.177
1	3	7	225.000	235.915	-0.711
1	3	8	2.000	2.210	-0.142
1	3	9	27.000	26.749	0.049
1	4	1	266.000	275.909	-0.597
1	4	2	0.000	0.023	-0.151
1	4	3	55.000	42.758	1.872
1	4	4	1913.000	1913.170	-0.004
1	4	5	4.000	5.889	-0.779
1	4	6	65.000	66.000	-0.123
1	4	7	371.000	352.341	0.994
1	4	8	338.000	345.517	-0.404
1	4	9	125.000	135.485	-0.901
1	5	1	0.000	0.027	-0.166
1	5	2	19.000	14.032	1.326
1	5	3	0.000	1.472	-1.213
1	5	4	1.000	0.948	0.054
1	5	5	365.000	365.024	-0.001
1	5	6	34.000	30.858	0.566
1	5	7	10.000	10.078	-0.025
1	5	8	0.000	0.630	-0.794
1	5	9	8.000	13.932	-1.589
1	6	1	0.000	0.001	-0.023
1	6	2	0.000	0.019	-0.138
1	6	3	0.000	0.039	-0.197
1	6	4	6.000	8.042	-0.720
1	6	5	7.000	8.819	-0.613

1	6	6	674.000	673.732	0.010
1	6	7	0.000	0.000	-0.016
1	6	8	8.000	3.986	2.011
1	6	9	0.000	0.326	-0.571
1	7	1	14.000	11.502	0.736
1	7	2	54.000	45.883	1.198
1	7	3	141.000	147.196	-0.511
1	7	4	84.000	100.740	-1.668
1	7	5	93.000	101.376	-0.832
1	7	6	6.000	6.342	-0.136
1	7	7	913.000	913.054	-0.002
1	7	8	13.000	15.958	-0.740
1	7	9	358.000	333.971	1.315
1	8	1	27.000	16.226	2.675
1	8	2	0.000	0.001	-0.024
1	8	3	0.000	0.064	-0.253
1	8	4	281.000	281.293	-0.017
1	8	5	14.000	14.955	-0.247
1	8	6	82.000	85.570	-0.386
1	8	7	44.000	39.421	0.729
1	8	8	736.000	735.861	0.005
1	8	9	225.000	235.629	-0.692
1	9	1	1.000	1.103	-0.098
1	9	2	53.000	63.681	-1.338
1	9	3	4.000	3.499	0.268
1	9	4	18.000	17.823	0.042
1	9	5	249.000	239.546	0.611
1	9	6	15.000	13.412	0.434
1	9	7	86.000	95.622	-0.984
1	9	8	41.000	32.305	1.530
1	9	9	505.000	505.025	-0.001
2	1	1	1193.000	1193.000	-0.000
2	1	2	0.000	0.021	-0.146
2	1	3	94.000	94.798	-0.082
2	1	4	461.000	467.161	-0.285
2	1	5	0.000	0.081	-0.285
2	1	6	0.000	0.150	-0.387
2	1	7	107.000	110.896	-0.370
2	1	8	60.000	58.311	0.221
2	1	9	37.000	27.548	1.801
2	2	1	0.000	0.244	-0.494
2	2	2	598.000	597.999	0.000
2	2	3	25.000	18.114	1.618
2	2	4	1.000	0.499	0.708
2	2	5	64.000	64.558	-0.069
2	2	6	0.000	0.014	-0.117
2	2	7	20.000	13.133	1.895
2	2	8	0.000	0.134	-0.366
2	2	9	35.000	48.263	-1.909

2	3	1	81.000	77.002	0.456
2	3	2	23.000	20.116	0.643
2	3	3	575.000	575.000	0.000
2	3	4	16.000	31.953	-2.822
2	3	5	7.000	10.301	-1.029
2	3	6	0.000	0.068	-0.260
2	3	7	195.000	182.348	0.937
2	3	8	3.000	2.842	0.094
2	3	9	28.000	28.360	-0.068
2	4	1	240.000	228.376	0.769
2	4	2	0.000	0.049	-0.220
2	4	3	30.000	44.258	-2.143
2	4	4	1815.000	1814.998	0.000
2	4	5	10.000	7.881	0.755
2	4	6	65.000	63.832	0.146
2	4	7	318.000	339.686	-1.177
2	4	8	296.000	287.216	0.518
2	4	9	163.000	150.778	0.995
2	5	1	0.000	0.145	-0.381
2	5	2	15.000	20.801	-1.272
2	5	3	6.000	4.252	0.848
2	5	4	3.000	3.057	-0.033
2	5	5	652.000	651.999	0.000
2	5	6	54.000	57.623	-0.477
2	5	7	28.000	27.836	0.031
2	5	8	3.000	2.213	0.529
2	5	9	44.000	37.075	1.137
2	6	1	0.000	0.005	-0.069
2	6	2	0.000	0.071	-0.266
2	6	3	0.000	0.183	-0.428
2	6	4	21.000	18.774	0.514
2	6	5	21.000	18.919	0.478
2	6	6	826.000	826.001	-0.000
2	6	7	0.000	0.003	-0.055
2	6	8	6.000	10.562	-1.404
2	6	9	2.000	1.445	0.462
2	7	1	12.000	14.998	-0.774
2	7	2	24.000	33.365	-1.621
2	7	3	136.000	128.667	0.646
2	7	4	117.000	97.500	1.975
2	7	5	101.000	91.266	1.019
2	7	6	9.000	8.587	0.141
2	7	7	1017.000	1016.999	0.000
2	7	8	24.000	20.596	0.750
2	7	9	301.000	329.039	-1.546
2	8	1	6.000	18.304	-2.876
2	8	2	0.000	0.002	-0.043
2	8	3	0.000	0.152	-0.389
2	8	4	214.000	213.878	0.008

```
2 8 5   17.000    16.024      0.244
2 8 6   77.000    72.864      0.484
2 8 7   42.000    47.297     -0.770
2 8 8   596.000   596.000     0.000
2 8 9   234.000   221.492     0.840
2 9 1   3.000     2.926       0.043
2 9 2   77.000    64.577      1.546
2 9 3   7.000     7.576      -0.209
2 9 4   32.000    32.180     -0.032
2 9 5   268.000   278.970    -0.657
2 9 6   22.000    23.862     -0.381
2 9 7   174.000   162.801     0.878
2 9 8   45.000    55.126     -1.364
2 9 9   670.000   670.000     0.000
*** LOG-LINEAR PARAMETERS ***
* TABLE YSE [or P(YSE)] *
effect   beta   exp(beta)
main     2.3933 10.9493
Y
1       -0.2152 0.8064
2        0.2152 1.2402
S
1       -0.1946 0.8232
2       -1.5028 0.2225
3        0.5331 1.7042
4        1.5935 4.9209
5       -0.4597 0.6315
6       -3.0731 0.0463
7        1.8026 6.0654
8        0.0335 1.0340
9        1.2675 3.5519
E
1       -1.0569 0.3475
2       -2.1596 0.1154
3       -0.1854 0.8308
4        1.1915 3.2919
5        0.5822 1.7899
6       -0.9257 0.3963
7        0.8424 2.3219
8        0.1749 1.1912
9        1.5365 4.6485
YS
1 1      0.0236 1.0239
1 2     -0.1086 0.8971
1 3      0.2682 1.3077
1 4      0.1995 1.2207
1 5     -0.2528 0.7767
1 6     -0.4398 0.6442
1 7      0.2123 1.2366
```

```
1 8       0.1297 1.1385
1 9      -0.0322 0.9683
2 1      -0.0236 0.9767
2 2       0.1086 1.1147
2 3      -0.2682 0.7647
2 4      -0.1995 0.8192
2 5       0.2528 1.2876
2 6       0.4398 1.5523
2 7      -0.2123 0.8087
2 8      -0.1297 0.8784
2 9       0.0322 1.0327
YE
1 1      -0.0869 0.9167
1 2       0.0383 1.0390
1 3       0.0007 1.0007
1 4       0.0794 1.0826
1 5       0.0715 1.0741
1 6      -0.0520 0.9493
1 7      -0.0432 0.9577
1 8      -0.0127 0.9874
1 9       0.0049 1.0050
2 1       0.0869 1.0908
2 2      -0.0383 0.9624
2 3      -0.0007 0.9993
2 4      -0.0794 0.9237
2 5      -0.0715 0.9310
2 6       0.0520 1.0534
2 7       0.0432 1.0442
2 8       0.0127 1.0128
2 9      -0.0049 0.9951
spe(SE,5a) [Y 1]
1         0.1026 1.1080
2         0.5720 1.7719
3         0.5388 1.7140
4         0.4015 1.4940
5         0.3212 1.3788
6         0.0363 1.0370
7         0.2733 1.3143
8         0.1714 1.1870
9        -0.0229 0.9773
Y [spe(SE,1a)]
1         1.0000
2         0.8587
spe(SE,1a) [Y]
1         6.4761 649.4330
2        -4.7050 0.0090
3         2.7337 15.3896
4         3.0792 21.7413
5        -6.3007 0.0018
```

6	-3.9785	0.0187
7	1.6683	5.3033
8	1.7326	5.6551
9	-1.9248	0.1459
10	7.9245	2.76E+0003
11	2.1759	8.8097
12	-3.5176	0.0297
13	2.8444	17.1909
14	-5.3992	0.0045
15	0.5534	1.7391
16	-3.9733	0.0188
17	2.8418	17.1468
18	2.7086	15.0083
19	3.6428	38.1984
20	-0.6070	0.5450
21	-1.2248	0.2938
22	-5.4635	0.0042
23	1.6849	5.3919
24	-2.3484	0.0955
25	2.7929	16.3284
26	-5.6242	0.0036
27	-0.0308	0.9697
28	2.3147	10.1216
29	-2.8516	0.0578
30	1.1963	3.3079
31	1.0944	2.9875
32	1.7118	5.5390
33	-3.9170	0.0199
34	3.2970	27.0319
35	-0.8944	0.4088
36	-2.7904	0.0614
37	3.7807	43.8448
38	2.9415	18.9438
39	0.0456	1.0466
40	-2.0900	0.1237
41	-5.0803	0.0062
42	-0.4986	0.6074
43	-1.7292	0.1774
44	2.1487	8.5734
45	2.8580	17.4274
46	8.8253	6.80E+0003
47	-7.7531	4.29E-0004
48	2.5554	12.8759
49	-0.6066	0.5452
50	1.7544	5.7800
51	0.9835	2.6737
52	-0.8513	0.4269
53	-0.2279	0.7962
54	-1.3681	0.2546

```
55       1.8247 6.2007
56      -1.5853 0.2049
57       1.5893 4.9002
58      -7.7185 4.45E-0004
59      -4.9052 0.0074
60       2.0274 7.5940
61      -0.2898 0.7484
62       3.0858 21.8851
63       0.5339 1.7056
64       4.0976 60.1968
```

Appendix E. LEM input for other models

```
*NA model
*Y = year transition, S = start type, E = end type
man 3
dim 2 9 9
lab Y S E
mod {YS,YS,fac(SE,9,Y,c)}
des {1 0 0 0 0 0 0 0 0
     0 2 0 0 0 0 0 0 0
     0 0 3 0 0 0 0 0 0
     0 0 0 4 0 0 0 0 0
     0 0 0 0 5 0 0 0 0
     0 0 0 0 0 6 0 0 0
     0 0 0 0 0 0 7 0 0
     0 0 0 0 0 0 0 8 0
     0 0 0 0 0 0 0 0 9}
*following models use the same setup except for mod { } specification

*Ro model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,3a)}
*Ru model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,3a),ass2(S,E,Y,2a)}
*Rx model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,3b)}
*Co model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,4a)}
*Cu model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,4a),ass2(S,E,Y,2a)}
*Cx model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,4b)}
*(R+C)o model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,3a),ass2(S,E,Y,4a)}
*(R+C)u model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,3a),ass2(S,E,Y,4a),ass2(S,E,Y,2a)}
*(R+C)x model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,3b),ass2(S,E,Y,4b)}
*RCo model
```

```
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,5a)}
*RCx model
mod {YS,YE,fac(SE,9,Y,c),ass2(S,E,Y,5b)}

*FI models use a different des[ ] specification
*FIo
mod {YS,YE,spe(SE,5a,Y,c,1},spe{SE,1a,Y,a)}
des[0 1]
*FIu
mod {YS,YE,spe(SE,5a,Y,c,1},spe{SE,1a,Y,a),ass2(S,E,Y,2a}
des[0 1]
```

Appendix F. R-Code for Creating Data Set

```
library(dplyr)
library(data.table)
library(readxl)
library(writexl)

##SAMPLING##
#load all metro- and micro- areas in the U.S. South as defined by the census from Social Explore
data <- read.csv("AllSouthernMSA_Race.csv")

data <- data%>%
  filter(!grepl('Micro', NAME)) #remove micropolitan areas
data <- data %>%
  filter(!grepl('Philadelphia',NAME))

#Find the percentage of each racial category in the U.S. South in 2010
(numbers from Social Explorer)
a <- 68706462/114555744 #60.0% White
b <- 21578475/114555744 #18.84% Black
c <- 18227508/114555744 #15.91% Latinx
d <- 3170814/114555744 #2.77% Asian

#Criterion: MSAs with at least one immigrant group greater than the regional share
data <- data %>%
  mutate(sample.dum = ifelse(Latinx/TotPop >= c | Asian/TotPop >= d, 1, 0))

sample <- data %>%
  filter(sample.dum==1) %>% select(Geo_CBSA, STATE, NAME, TotPop, Latinx, Asian)
list(sample$Geo_CBSA)

#Classifying tracts in 2010, 2000, and 1990, using tract-level race data from Social Explorer
##2010 Classification##
data2010 <- read.csv("UStracts_Race2010.csv")
data2010 <- data2010 %>%
  filter(Geo_CBSA %in%
          c('22900', '47900', '15980', '18880', '23540',
            '27260', '29460', '33100', '34940', '36740',
            '45300', '12020', '12060', '19140', '23580',
            '12580', '16740', '20500', '24660', '39580',
            '36420', '10180', '11100', '12420', '15180',
            '17780', '18580', '19100', '21340', '26420',
            '28660', '29700', '31180', '32580', '33260',
            '36220', '41660', '41700', '46340', '47020',
            '47380', '13980', '16820', '40060', '47260'))%>%
  select("Geo_FIPS","Geo_NAME","Geo_QName","Geo_REGION","Geo_DIVISION",
         "Geo_STATE","Geo_COUNTY", "Geo_TRACT", "Geo_CBSA",
         "TotPop", "White", "Black", "AIAN", "Asian", "NHPI", "Latinx")
```

```
w.avg.2010 <- sum(data2010$White)/sum(data2010$TotPop)
b.avg.2010 <- sum(data2010$Black)/sum(data2010$TotPop)
l.avg.2010 <- sum(data2010$Latinx)/sum(data2010$TotPop)
a.avg.2010 <- sum(data2010$Asian)/sum(data2010$TotPop)
df2010.50 <- data2010 %>%
  mutate(year = 2010,
         W.type = ifelse(White/TotPop >= .50*(w.avg.2010),1,0),
         B.type = ifelse(Black/TotPop >= .50*(b.avg.2010),1,0),
         L.type = ifelse(Latinx/TotPop >= .50*(l.avg.2010),1,0),
         A.type = ifelse(Asian/TotPop >= .50*(a.avg.2010),1,0))
df2010.50 <- na.omit(df2010.50)
df2010.50 <- df2010.50 %>%
  mutate(W = ifelse(W.type == 1 & B.type == 0 & A.type == 0 & L.type == 0,1,0),
         B = ifelse(W.type == 0 & B.type == 1 & A.type == 0 & L.type == 0,1,0),
         L = ifelse(W.type == 0 & B.type == 0 & A.type == 0 & L.type == 1,1,0),
         A = ifelse(W.type == 0 & B.type == 0 & A.type == 1 & L.type == 0,1,0),
         WB = ifelse(W.type == 1 & B.type == 1 & A.type == 0 & L.type == 0,1,0),
         WA = ifelse(W.type == 1 & B.type == 0 & A.type == 1 & L.type == 0,1,0),
         WL = ifelse(W.type == 1 & B.type == 0 & A.type == 0 & L.type == 1,1,0),
         BA = ifelse(W.type == 0 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
         BL = ifelse(W.type == 0 & B.type == 1 & A.type == 0 & L.type == 1,1,0),
         AL = ifelse(W.type == 0 & B.type == 0 & A.type == 1 & L.type == 1,1,0),
         WBA = ifelse(W.type == 1 & B.type == 1 & A.type == 1 & L.type == 0,1,0),
         WBL = ifelse(W.type == 1 & B.type == 1 & A.type == 0 & L.type == 1,1,0),
         WLA = ifelse(W.type == 1 & B.type == 0 & A.type == 1 & L.type == 1,1,0),
         BLA = ifelse(W.type == 0 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
         WBLA = ifelse(W.type == 1 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
         Ntype = ifelse(W == 1, "W", ifelse(B ==1, "B", ifelse(L ==1, "L", ifelse(A ==1, "A",
                 ifelse(WB ==1, "WB", ifelse(WL ==1, "WL", ifelse(WA ==1, "WA",
                 ifelse(BL ==1, "BL", ifelse(BA ==1, "BA",
                 ifelse(AL ==1, "LA",
                 ifelse(WBL ==1, "WBL", ifelse(WBA==1, "WBA", ifelse(WLA ==1, "WLA",
                 ifelse(BLA==1, "BLA","WBLA")))))))))))))))

##2000 Classification
data2000 <- read.csv("Sample2000.2.csv")
data2000 <- data2000 %>%
  select("Geo_FIPS","Geo_NAME","Geo_QName", "Geo_STATE","Geo_COUNTY", "Geo_CT",
         "TotPop", "White", "Black", "AIAN", "Asian", "NHPI", "Latinx")
data2000 <- na.omit(data2000)
w.avg.2000 <- sum(data2000$White)/sum(data2000$TotPop)
b.avg.2000 <- sum(data2000$Black)/sum(data2000$TotPop)
l.avg.2000 <- sum(data2000$Latinx)/sum(data2000$TotPop)
a.avg.2000 <- sum(data2000$Asian)/sum(data2000$TotPop)
df2000.50 <- data2000 %>%
  mutate(year = 2000,
         W.type = ifelse(White/TotPop >= .50*(w.avg.2000),1,0),
         B.type = ifelse(Black/TotPop >= .50*(b.avg.2000),1,0),
         L.type = ifelse(Latinx/TotPop >= .50*(l.avg.2000),1,0),
```

```
         A.type = ifelse(Asian/TotPop >= .50*(a.avg.2000),1,0))
df2000.50 <- na.omit(df2000.50)
df2000.50 <- df2000.50 %>%
  mutate(W = ifelse(W.type == 1 & B.type == 0 & A.type == 0 & L.type == 0,1,0),
         B = ifelse(W.type == 0 & B.type == 1 & A.type == 0 & L.type == 0,1,0),
         L = ifelse(W.type == 0 & B.type == 0 & A.type == 0 & L.type == 1,1,0),
         A = ifelse(W.type == 0 & B.type == 0 & A.type == 1 & L.type == 0,1,0),
         WB = ifelse(W.type == 1 & B.type == 1 & A.type == 0 & L.type == 0,1,0),
         WA = ifelse(W.type == 1 & B.type == 0 & A.type == 1 & L.type == 0,1,0),
         WL = ifelse(W.type == 1 & B.type == 0 & A.type == 0 & L.type == 1,1,0),
         BA = ifelse(W.type == 0 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
         BL = ifelse(W.type == 0 & B.type == 1 & A.type == 0 & L.type == 1,1,0),
         AL = ifelse(W.type == 0 & B.type == 0 & A.type == 1 & L.type == 1,1,0),
         WBA = ifelse(W.type == 1 & B.type == 1 & A.type == 1 & L.type == 0,1,0),
         WBL = ifelse(W.type == 1 & B.type == 1 & A.type == 0 & L.type == 1,1,0),
         WLA = ifelse(W.type == 1 & B.type == 0 & A.type == 1 & L.type == 1,1,0),
         BLA = ifelse(W.type == 0 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
         WBLA = ifelse(W.type == 1 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
         Ntype = ifelse(W == 1, "W", ifelse(B ==1, "B", ifelse(L ==1, "L", ifelse(A ==1, "A",
                 ifelse(WB ==1, "WB", ifelse(WL ==1, "WL", ifelse(WA ==1, "WA",
                 ifelse(BL ==1, "BL", ifelse(BA ==1, "BA",
                 ifelse(AL ==1, "LA",
                 ifelse(WBL ==1, "WBL", ifelse(WBA==1, "WBA", ifelse(WLA ==1, "WLA",
                 ifelse(BLA==1, "BLA","WBLA")))))))))))))))

##1990 Classification##
data1990 <- read.csv("Sample1990.2.csv")
data1990 <- data1990 %>%
  select("Geo_FIPS","Geo_NAME","Geo_QName", "Geo_STATE","Geo_COUNTY", "Geo_CT",
         "TotPop", "White", "Black", "AIAN", "Asian", "Latinx")
data1990 <- na.omit(data1990)
w.avg.1990 <- sum(data1990$White)/sum(data1990$TotPop)
b.avg.1990 <- sum(data1990$Black)/sum(data1990$TotPop)
l.avg.1990 <- sum(data1990$Latinx)/sum(data1990$TotPop)
a.avg.1990 <- sum(data1990$Asian)/sum(data1990$TotPop)
df1990.50 <- data1990 %>%
  mutate(year = 1990,
         W.type = ifelse(White/TotPop >= .50*(w.avg.1990),1,0),
         B.type = ifelse(Black/TotPop >= .50*(b.avg.1990),1,0),
         L.type = ifelse(Latinx/TotPop >= .50*(l.avg.1990),1,0),
         A.type = ifelse(Asian/TotPop >= .50*(a.avg.1990),1,0))
df1990.50 <- na.omit(df1990.50)
df1990.50 <- df1990.50 %>%
  mutate(W = ifelse(W.type == 1 & B.type == 0 & A.type == 0 & L.type == 0,1,0),
         B = ifelse(W.type == 0 & B.type == 1 & A.type == 0 & L.type == 0,1,0),
         L = ifelse(W.type == 0 & B.type == 0 & A.type == 0 & L.type == 1,1,0),
         A = ifelse(W.type == 0 & B.type == 0 & A.type == 1 & L.type == 0,1,0),
         WB = ifelse(W.type == 1 & B.type == 1 & A.type == 0 & L.type == 0,1,0),
         WA = ifelse(W.type == 1 & B.type == 0 & A.type == 1 & L.type == 0,1,0),
```

```
        WL = ifelse(W.type == 1 & B.type == 0 & A.type == 0 & L.type == 1,1,0),
        BA = ifelse(W.type == 0 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
        BL = ifelse(W.type == 0 & B.type == 1 & A.type == 0 & L.type == 1,1,0),
        AL = ifelse(W.type == 0 & B.type == 0 & A.type == 1 & L.type == 1,1,0),
        WBA = ifelse(W.type == 1 & B.type == 1 & A.type == 1 & L.type == 0,1,0),
        WBL = ifelse(W.type == 1 & B.type == 1 & A.type == 0 & L.type == 1,1,0),
        WLA = ifelse(W.type == 1 & B.type == 0 & A.type == 1 & L.type == 1,1,0),
        BLA = ifelse(W.type == 0 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
        WBLA = ifelse(W.type == 1 & B.type == 1 & A.type == 1 & L.type == 1,1,0),
        Ntype = ifelse(W == 1, "W", ifelse(B ==1, "B", ifelse(L ==1, "L", ifelse(A ==1, "A",
                ifelse(WB ==1, "WB", ifelse(WL ==1, "WL", ifelse(WA ==1, "WA",
                ifelse(BL ==1, "BL", ifelse(BA ==1, "BA",
                ifelse(AL ==1, "LA",
                ifelse(WBL ==1, "WBL", ifelse(WBA==1, "WBA", ifelse(WLA ==1, "WLA",
                ifelse(BLA==1, "BLA","WBLA"))))))))))))))

##RESHAPING DATA
df1990.50 <- as.data.table(df1990.50)
df2000.50 <- as.data.table(df2000.50)
df2010.50 <- as.data.table(df2010.50)
dfLong <- rbind(df1990.50,df2000.50,df2010.50, fill=TRUE)

#removing tracts with little or no population
dfLong <- dfLong %>%
  filter(!grepl('980', Geo_NAME))
dfLong <- dfLong %>%
  filter(!Geo_FIPS %in%
         c(12086003705, 12086006709, 12086009043, 12086009044, 12086009046,
           12086009047, 12086011008, 12086011009, 12099007835, 12101032106,
           37063001503, 48085031657, 51059481101, 11001006202, 12086009040,
           48339691700, 48201455300, 13121003700))

dfLong <- as.data.table(dfLong)
cols <- c("Ntype", "TotPop", "White", "Black", "Asian", "Latinx")
dfWide <- dcast(dfLong, Geo_FIPS+Geo_NAME+Geo_QName~year, value.var=c(cols))

#COLLAPSE CATEGORIES
dfLong2 <- dfLong %>%
  mutate(Ntype = recode(Ntype,
                        "W" = 1,
                        "B" = 2,
                        "L" = 3,
                        "A" = 4,
                        "WB" = 5,
                        "WL" = 6,
                        "WA" = 7,
                        "BL" = 8,
                        "BA" = 9,
                        "LA" = 10,
```

```
                        "WBL" = 11,
                        "WBA" = 12,
                        "WLA" = 13,
                        "BLA"= 14,
                        "WBLA" = 15))
#collapse categories - L,A,LA (all immigrant - 10); WL, WA (white single immigrant - 7);
BL, BA (black single immigrant -9); WBL, WBA (semi-global - 12)
dfLong2 <- dfLong2 %>%
  mutate(Ntype = recode(Ntype,
                        "3" = 10,
                        "4" = 10,
                        "6" = 7,
                        "7" = 7,
                        "8" = 9,
                        "9" = 9,
                        "11" = 12,
                        "12" = 12))
dfLong2 <- as.data.table(dfLong2)
cols <- c("Ntype", "TotPop", "White", "Black", "Asian", "Latinx")
dfWide2 <- dcast(dfLong2, Geo_FIPS+Geo_QName+Geo_STATE~year, value.var=c(cols))
```