An Assessment of Developmental Trajectory of Baby Boomers in the United States - A Latent Growth Curve Modeling Application

Repeated measures over time are often of interest to marketers (Lessne & Hanumara, 1988). Many important marketing issues deal with the study of change in marketing variables based on an analysis of repeated measurements of entities (demographics, consumers, salespeople, companies, brands, etc.) observed at different points in time or at different levels of an independent variable (Steenkamp & Baumgartner, 2000). The growth analysis of demographic variables such as population of a certain target demographic is of utmost importance, especially in the context of the United States, as it is fast becoming an older nation. An understanding of this demographic change or demographic shift, especially from a consumer behavior standpoint, hence, is of vital importance to academics and to practitioners in the fields of marketing and consumer behavior. The Baby Boomer generation (people born in the post-World War II era between 1946 and 1964) in the US is edging into retirement. This demographic shift will create the need for new services and infrastructure changes nationwide, particularly in areas such as transportation, housing, and other high involvement product and service categories. The Baby Boomer generation was recently at 80 million (Lancaster & Stillman, 2002). More people were 65 years and over in 2010 than in any previous census. Between 2000 and 2010, the population 65 years and over increased at a faster rate (15.1 %) than the total population (9.7%). In 2012, baby boomers held more than 90% of US's net worth, and 78% of all its financial assets (Faleris, 2012). Their ethnic composition has changed too. In particular, there has been an increase in the proportion of Hispanic population. As larger numbers of males and females reach age 65 years and over, it becomes increasingly important to understand this population as well as the implications population aging has for various family, social, and economic aspects of society (U.S. Census Bureau, 2011). These Baby Boomers, who generally have low incomes, high reliance on social security, are constrained to stay in a location, and have longer retirements, will act or react to mitigate such changes in their lives (Clayton, 2012). In particular, the importance of identity will drive consumption patterns, social norms will shape consumer behavior, companies will adopt stances to de-market (by creating barriers), and there will be a significant attitude-behavior gap with respect to tempering the real-world impacts of observed consumption attitudes (Bowerman & Markowitz, 2012). An understanding of this viable, non-monolithic segment, hence, would enable marketers and policy-makers to devise strategies to pre-emptively avoid, pro-actively influence, and/or reactively mitigate its consumption outcomes (Lee et al., 2009). So, an understanding of the demographic growth curve and trajectories of older people in the United States over the past few years will be vital.

Traditionally, such longitudinal data have been analyzed using Ordinary Least Squares (OLS) regression pooled across repeated measurements (Steenkamp & Baumgartner, 2000). A majority of researchers use ANOVA, which is not appropriate, because such longitudinal data are autocorrelated. Timm (1980, p.74) states that *"the standard MANOVA model has several limitations if an experimenter wants to analyze and fit growth curves to the average growth of a population over time."* Such methods require observations that have the same variance and a common correlation for all pairs. Such symmetry is rarely encountered in the real world (Steenkamp & Baumgartner, 2000). Given the importance of analyzing demographic growth trajectories from a point-of-view that matches the real world more closely, the objective of the present study was to attempt to analyze nationwide county-level data for the population over 60 years of age in the 50 states in USA; in which the latent variable "population growth" was operationalized by actual population counts. In a model building approach, two and three-factor latent growth curve models were explored (for "all" and "Hispanic" populations) to reveal realistic growth patterns. In line with these objectives, the research questions addressed by this study were: (1) What has the growth pattern of the population of people above 60 years of age been in the United States in the period between 2000 and 2012? Has it been linear or quadratic? (2) What has the growth pattern of the Hispanic population of people above 60 years of age been in the United States in the period between 2000 and 2012? Has it been linear or quadratic?

The following is a brief literature review of the topic of interest, and a discussion of the methods, results, and limitations of the present study, and a discussion of avenues of future research related to this topic and methodology.

Literature Review

"How much do you agree or disagree with the following statement: We'd all be better off if we consumed less." That is one survey item reported in the study by University of Oregon researchers Markowitz and Bowerman (2012). Such examination of the public's beliefs about consumption, and how much consumption is enough, has been approached from the perspective that consumers make the decision to consume less or more (in this case, less) based on a voluntary choice. The point that such studies highlight for policy makers is that Americans are ready to "deconsume" for the sake of the environment, and their personal well-being, cutting back purchases of material goods, and especially reducing their emissions of greenhouse gases. Such ideas of "deconsumption," defined by Markowitz and Bowerman (2012) as *"making do with less,"* miss one major component – will. Deconsumption, along with constructs such as "downshifting" have been treated in literature as voluntary functions of consumers' behavior. So, different from conventional definitions of (voluntary) deconsumption, my dissertation will consider the role of free will and explore deconsumption as a continuum between voluntary and involuntary, the latter defined as *"the phenomenon exhibited by individuals wherein they are forced to consume less or not at all, some products, services, or experiences they used to consume in the past."*

Given that consumption (and the lack of it) has been deemed as a voluntary choice, and given the dearth of literature and scholarship in the understanding of involuntary deconsumption, there is a call for scholarship on this construct. In particular, the exploration of this concept among the Baby Boomer generation (people born in the post-World War II era between 1946 and 1964), which is 80 million strong, and growing in the USA (Lancaster & Stillman, 2002), is vital from a marketing strategy perspective. Scales in marketing literature do not address involuntary deconsumption. The only scale that comes close is the Voluntary Simplicity Scale (VSS) (Cowles & Crosby, 1986; Leonard-Barton, 1981). Within the larger picture of deconsumption, the justification of the developmental patterns of the Baby Boomer generation across the past few years is important. It should be noted that some developing parts of the world are exhibiting an increase in materialism. For example, between 1980 and 2005, China used more cement per capita as its citizens increasingly could afford and then demand better housing (US Census Bureau, 2011). Countries such as India have fast growing economies. Clocked at a growth rate of 8.3% in 2010, India is fast on its way to becoming a large and globally important consumer economy. The Indian middle class was estimated to be 250 million people in 2007, and will reach 600 million by 2030 (Farrell & Beinhocker, 2007).

It's a different story in the United States though. The Baby Boomer generation (people born in the post-World War II era between 1946 and 1964) is edging into retirement. This demographic shift will create the need for new services and infrastructure changes nationwide, particularly in areas such as transportation, housing, and other high involvement product and service categories. The Baby Boomer generation was recently at 80 million (Lancaster & Stillman, 2002). This older population is an important segment of the United States' population. More people were 65 years and over in 2010 than in any previous census. Between 2000 and 2010, the population 65 years and over increased at a faster rate (15.1 %) than the total population (9.7%). As larger numbers of males and females reach age 65 years and over, it becomes increasingly important to understand this population as well as the implications population aging has for various family, social, and economic aspects of society (U.S. Census Bureau, 2011). These Baby Boomers, who generally have low incomes (the median income for people age 65 and older was $27,707 for males and $15,362 for females in 2011), high reliance on social security (the most common source of retirement income is social security, and 86% of people age 65 and older receive monthly payments, and will be the first generation to overwhelmingly not receive some sort of guaranteed benefits from employers), are constrained to stay in a location (most people retire where they spent the final years of their career, between 2011 and 2012, only 3% of people age 65 and older moved), and have longer retirements (the average life expectancy for people turning age 65 is an additional 20.4 years for women and 17.8 years for men, older women significantly outnumbering retired men) (Brandon, 2013); and will act to mitigate such changes in their lives (Clayton, 2012). The growth in the Hispanic population is also noteworthy. In particular, the importance of identity will drive consumption patterns, social norms will shape consumer behavior, companies will adopt stances to de-market (by creating barriers), and there will be a significant attitude-behavior gap with respect to tempering the real-world impacts of observed deconsumption attitudes of Baby Boomers (Bowerman & Markowitz, 2012).

Given the growing importance of studying Baby Boomers in the United States from a marketing strategy and policy point of view, and considering how little attention has been given to the construct of deconsumption from a holistic (continuum of voluntary and involuntary deconsumption) perspective, and given the importance of understanding the population development trajectory of this population, the current study was conducted. It was a latent growth curve modeling exploration of county-level data of population of people above the age of 60 years in the 50 states in the USA. The traditional statistics presented in studies of demographic change analyzing longitudinal data use Ordinary Least Squares (OLS) regression pooled across repeated measurements (Steenkamp & Baumgartner, 2000), and ANOVA; which are not appropriate, because such longitudinal data are autocorrelated (Timm, 1980), and beg for a more realistic latent growth curve modeling technique for analyzing such data. In answering the research questions of the developmental pattern of the general and Hispanic population of people above 60 years of age been in the United States in the period between 2000 and 2012, the following were the research hypotheses:

H_{01}: There was no growth in the Baby Boomer population in the United States between the years 2000 and 2012.

H_{11}: There was a linear (or quadratic) growth in the Baby Boomer population in the United States between the years 2000 and 2012.

H_{02}: There was no growth in the Hispanic Baby Boomer population in the United States between the years 2000 and 2012.

H_{12}: There was a linear (or quadratic) growth in the Hispanic Baby Boomer population in the United States between the years 2000 and 2012.

Method

Traditional autoregressive models depicting change over time have several shortcomings. The means of the measured variables are assumed to be zero (resulting in information loss), there is a lack of generalization to two or more points in time, predictors are eliminated, and the autoregressive effect is questionable as a true causal effect (Duncan et al., 2006). To address these shortcomings, an integrated latent growth curve developmental model (a multi wave model) was employed to answer the research questions above, and to test the hypotheses. In particular, two- and three-factor latent growth curve models with the variable of "population development" operationalized using population figures across 13 time points (from 2000 to 2012) on a county level were run. However, the annual data from 13 time points tended to be highly correlated, and in particular, data within a 3-year range showed minimal variation across counties. Hence, in the final analysis, data from 5 time points (years 2000, 2003, 2006, 2009, and 2012) was used.

Participants

Data from the AGing Integrated Database (AGID), an on-line query system based on population characteristics from the Census Bureau Population (Administration on Aging, 2014), covering residents age 60 and older, of the 50 United States and the District of Columbia, across the years 2000 to 2012 was used for this project. The database contained annual county-level resident population estimates by age groups, and Hispanic origin, with full access to results from national surveys of recipients of Older Americans Act services produced by the Census Bureau.

Research Design

Two- and three-factor latent growth curve models with the variable of "population development" operationalized using population figures across the 5 of the 13 time points over 3-year periods (from 2000 to 2012 – 2000, 2003, 2006, 2009, and 2012) on a county level from the AGID was run. Two-factor unspecified LGM and three-factor polynomial LGMs were fitted for data on the all level, and on the Hispanic level.

Measures

This study used secondary data collected by the Census Bureau and archived by the AGID. Houston (2004) supports the idea of secondary data usage as an alternative for assessment in marketing studies. By employing secondary data proxies, researchers can avail themselves to new sources of data and can shed new light on or provide important corroborating evidence to established streams of research that have relied on a limited variety of methodological approaches. Population development at the county level was operationalized by numbers comprising a total of 40,833 data points pertaining to 3,143 counties in the 50 states and DC from the 13 years. Such county-level data makes for the analysis of statistically equivalent entities within the context of legally defined political and administrative units of the United States serving as the primary geographic units for which the Bureau of the Census reports data (Geographic Areas Reference Manual, 1994). For more details on the number of counties within each state used for this study, see Table 1.

Procedure & Data Analysis

The AGing Integrated Database (AGID) allowed for production of tabular data, at the level of detail most suited for the needs of this project. It provided a single, user friendly source for a variety of information. It provided full access to results from national surveys of recipients of Older Americans Act services produced by the Census Bureau. It proved to be a powerful tool for producing detailed, multi-year tables. The individual survey data files were provided in CSV formats. Since AMOS 20 (Arbuckle, 2011) software was used to analyze the SEM data, the CSV files were cleaned and prepared as "single record per county" data across years, was converted into SPSS files, and further analyses were carried on using IBM SPSS 20.0 (IBM Corp., 2011). Before the models could be run, the data was used to draw spaghetti plots in order to get a visual feel of the growth trajectories through the longitudinal data, showing individual tracings for each subject (counties, in the present case). It is to be noted that due to the sheer volume of data and the number of counties (3,143) in the dataset, the spaghetti plots did not run in the first attempt. So, counties were randomly selected from randomly selected states (six in all – California, Colorado, Georgia, Massachusetts, New York, and Texas). Out of these, spaghetti plots were produced for data on the all level, and pertaining to the Hispanic population (consisting 1,624 data points). Two- and three-factor latent growth curve models with the variable of "population development" operationalized using population figures across 5 time points (2000, 2003, 2006, 2009, and 2012) on a county level from the AGID was then run. The evaluations of model fit, as is the common approach to SEM, was done using measures such as the default model chi-square, chi-square difference tests, AIC, BIC, CFI, NFI, and RMSEA.

Results

Spaghetti Plots

The spaghetti plot (all level), shown in Figure 1, revealed that the baby boomer population was not just at a growth trajectory in the United States, it was on a growth that looked like linear, and possibly, even quadratic. Many of the counties fell in the low-growth band, but then again, many fell in the medium range of growth too. Some demonstrated dramatic growth, especially counties in California and Texas. The spaghetti plot (for Hispanics), shown in Figure 2, also revealed that the Hispanic baby boomer population was not just at a growth trajectory in the United States, it was on a growth that looked like linear, and most possibly, quadratic. Compared to the data at all-level, many more counties fell in the medium-to-high range of growth. More than a few counties demonstrated dramatic growth. Visually speaking, both the spaghetti plots warranted and justified that this data was suitable to a latent growth curve modeling approach of analysis.

Descriptive Data

The standard deviations of population figures across the five time points were consistently high. The means consistently increased across the years ($p<.001$), and so did the standard deviations ($p<.001$). The correlations were strong and positive. This was truer of the Hispanic data than of the all-level data. In fact, many of the counties started with zero, as far as Hispanic population was concerned. A snapshot is provided in Tables 2a and 2b.

Latent Growth Curve Models – All

Aging data from 3,143 counties across the United States was used for this analysis. In a model-building approach, an unspecified (and fixed) two-factor model, and a three-factor polynomial LGM were run. SEM was used to explore the growth trajectories of the national baby boomer population across the five time points.

Model 1 (Two-Factor Unspecified LGM). In this model, factor loadings on the slope factor were fixed at one (T1), three (T2), six (T3), nine (T4), and twelve (T5). Factor loadings for the intercepts were set to be constant. Since the same measure was repeated over time, the error variances across the time points were set to be constant, with e2 and e4 set to zero. The model estimated eight parameters, which included means and variances for intercept and slope factors, covariance between slope and intercept, and some of the constant error variances across the time points. With twelve degrees of freedom, the model was determined as over-identified. Fitting the LGM to the data resulted in a mean intercept value of M = 14108.63 (p<.001), and the mean slope value was M = 390.25 (p<.001). The intercept variance, and the variance of the latent slope showed substantial variation among counties in their initial and baby boomer population growth rate across the time points. A significant relationship between the intercept and the slope indicated that counties with higher number of baby boomers tended to grow faster in their baby boomer population across the time points. The chi-square test statistic (12504.70, p<.001), an RMSEA value of .576, NFI and CFI values of .863, and a high chi-square/df value (1042.06) reflected a non-fitting model. See Figure 4a for the model and its estimates.

Model 2 (Two-Factor Unspecified LGM With One Slope Loading Free to Estimate). In this model, four loadings on the slope factor were fixed at one (T1), three (T2), six (T3), and nine (T4), and T5 was left free to be estimated. Factor loadings for the intercepts were set to be constant. Since the same measure was repeated over time, the error variances across the time points were set to be constant, with e4 set to zero. The model estimated nine parameters, which included means and variances for intercept and slope factors, covariance between slope and intercept, one of the loadings of slope, and some of the constant error variances across the time points. With eleven degrees of freedom, the model was determined as over-identified. Fitting the LGM to the data resulted in a mean intercept value of M = 14108.63 (p<.001), and the mean slope value was M = 390.25 (p<.001), identical to the previous model (as expected). The unconstrained loading for the slope factor to the T5 population estimate was estimated at 13.41. This was not significantly different from 12, and indicated linear growth. The intercept variance, and the variance of the latent slope showed substantial variation among counties in their initial and baby boomer population growth rate across the time points. A significant relationship between the intercept and the slope indicated that counties with higher number of baby boomers tended to grow faster in their baby boomer population across the time points. The chi-square test statistic (10974.20, p<.001), an RMSEA value of .563, NFI and CFI values of .880, and a high chi-square/df value (997.66) reflected a non-fitting model (although better than the first one). See Figure 3 for the model and its estimates.

Model 3 (Three-Factor Polynomial LGM With Fixed Quadratic Loadings). In the three-factor polynomial model, all regression paths were fixed at values that represented polynomial contrasts used to identify scales for intercept, linear, and quadratic variables. It was assumed that the scores at all five time points were measured without errors. Therefore, the error means were fixed to zero. The error variances were freely estimated. Mean linear factor, *M* = 152.09, and the mean quadratic value, *M* = 21.37, were significant ($p<.001$). Additionally, the variances of the developmental parameters were different from zero ($p<.001$). The significant variance results indicated substantial variation among baby boomer population across the time points. Although the RMSEA value was .412 (better than previous models, though), a better chi-square test statistic (3210.56, $p<.001$), NFI and CFI values of .965, and a lower chi-square/df value (535.09) reflected a better fitting model compared to the previous models. However, the chi-square difference test was significant. So, the Two-Factor Unspecified LGM (with last 1 slope loading free to estimate) was deemed as the best fit for the population data on the all-level (see Table 3a for a comparative snapshot of the models discussed above).

Latent Growth Curve Models – Hispanic

Hispanic aging data from 3,143 counties across the United States was used for this analysis. In a model-building approach, an unspecified (and fixed) two-factor model, and a three-factor polynomial LGM were run. SEM was used to explore the growth trajectories of the national baby boomer population across the five time points.

Model 1 (Two-Factor Unspecified LGM). In this model, factor loadings on the slope factor were fixed at one (T1), three (T2), six (T3), nine (T4), and twelve (T5). Factor loadings for the intercepts were set to be constant. Since the same measure was repeated over time, the error variances across the time points were set to be constant, with e1 and e3 set to zero. The model estimated eight parameters, which included means and variances for intercept and slope factors, covariance between slope and intercept, and some of the constant error variances across the time points. With twelve degrees of freedom, the model was determined as over-identified. Fitting the LGM to the data resulted in a mean intercept value of *M* = 800.59 ($p<.001$), and the mean slope value was *M* = 46.89 ($p<.001$). The intercept variance, and the variance of the latent slope showed substantial variation among counties in their initial and baby boomer population growth rate across the time points. A significant relationship between the intercept and the slope indicated that counties with higher number of baby boomers tended to grow faster in their baby boomer population across the time points. The chi-square test statistic (14920.29, $p<.001$), an RMSEA value of .629, NFI and CFI values of .844, and a high chi-square/df value (1243.36) reflected a non-fitting model.

Model 2 (Two-Factor Unspecified LGM With Three Slope Loadings Free to Estimate). In this model, two loadings on the slope factor were fixed at one (T1), and three (T2). T3, T4, and T5 were left free to be estimated. Factor loadings for the intercepts were set to be constant. Since the same measure was repeated over time, the error variances across the time points were set to be constant, with e1 and e4 set to zero. The model estimated eleven parameters, which included means and variances for intercept and slope factors, covariance between slope and intercept, three of the loadings of slope, and some of the constant error variances across the time points. With eleven degrees of freedom, the model was determined as over-identified. Fitting the LGM to the data resulted in a mean intercept value of *M* = 800.59 ($p<.001$), and the mean slope value was *M* = 45.39 ($p<.001$), identical to the previous model (as expected). The unconstrained loadings for the slope factor to the T3, T4, and T5 populations were estimated at 6.20, 10.48, and 15.23 respectively. These were not significantly different from 6, 9, and 12 (respectively), and indicated linear growth. The intercept variance, and the variance of the latent slope showed substantial variation among counties in their initial and baby boomer population growth rate across the time points. A significant relationship between the intercept and the slope indicated that counties with higher number of baby boomers tended to grow faster in their baby boomer population across the time points. Although the RMSEA value was .354, the chi-square test statistic (3553.94, p<.001), NFI and CFI values of .963, and a low chi-square/df value (394.88) reflected a fairly well-fitting model, especially compared to model 1 above.

Model 3 (Three-Factor Polynomial LGM With Fixed Quadratic Loadings). In the three-factor polynomial model, all regression paths were fixed at values that represented polynomial contrasts used to identify scales for intercept, linear, and quadratic variables. It was assumed that the scores at all five time points were measured without errors. Therefore, the error means were fixed to zero. The error variances were freely estimated. Mean linear factor, M = 33.91, and the mean quadratic value, M = 2.23, were significant (p<.001). Additionally, the variances of the developmental parameters were different from zero (p<.001). The significant variance results indicated substantial variation among baby boomer population across the time points. Although the RMSEA value was .424 (almost identical to the two-factor model, and much better than model 1), a chi-square test statistic of 4523.51 (p<.001), NFI and CFI values of .953, and a low chi-square/df value (565.44) reflected an acceptable fit. Most importantly, the chi-square difference test (compared to the two-factor model) was significant. So, the Three-Factor Polynomial LGM was deemed as the best fit for the Hispanic baby boomer population data (see Table 3b for a comparative snapshot of the models discussed above). Also, see Figure 4 for the polynomial model and its estimates.

Conclusions & Discussion

The spaghetti plots suggested at least a linear growth trajectory of the baby boomer population in the United States across 2000-2012, especially the Hispanic baby boomer population. Many of the counties fell in the low-growth band, but then again, many fell in the medium range of growth too. Some demonstrated dramatic growth, especially counties in California and Texas. The spaghetti plots warranted and justified that this data was suitable to a latent growth curve modeling approach of analysis. On a descriptive level, the standard deviations of population figures across the five time points were consistently high. The means consistently increased across the years, and so did the standard deviations. The correlations were strong and positive. This was truer of the Hispanic data than of the all-level data. In fact, many of the counties started with zero, as far as Hispanic population was concerned. This was, again, a clear indication of growth. The growth curve modeling approach revealed that for the baby boomer population on the all-level, a two-factor unspecified LGM (with last 1 slope loading free to estimate) was deemed as the best fit. This showed a linear growth in the overall baby boomer population in the country in the period between 2000 and 2012. As far as the Hispanic population of baby boomers was concerned, the modeling exercise showed that a three-factor polynomial LGM was deemed as the best fit. Although the linear model fit better than the quadratic one, the chi-square difference test and acceptable values of fit suggested a possibility of quadratic growth in the overall baby boomer Hispanic population in the country in the period between 2000 and 2012. So, the null hypotheses were rejected, and the conclusions were:

H_{11}: There was a linear growth in the overall Baby Boomer population in the United States between the years 2000 and 2012.

H_{12}: There was a quadratic growth in the Hispanic Baby Boomer population in the United States between the years 2000 and 2012.

These findings have vital implications to the study and importance of deconsumption among the baby boomer population. Understanding the deconsumption stories of these people in the United States (especially the older Hispanics), and devising ways to make reconsumption of some product/service/brand categories should be priority for marketing managers and the industry alike. This might be especially true of certain states such as Florida, California, Arizona, and Texas, where the baby boomer population seems to have exploded. This study did not analyze data on state level to make a confident claim of the above. Future studies should be targeted at assessing the growth trajectories in various states, so that more focused and targeted strategies could be suggested to marketing managers and policy-makers across the United States.

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Table 1

Number of Counties in the USA by State

Sl. No.	State	Number of Counties
1	Alabama	67
2	Alaska	25
3	Arizona	15
4	Arkansas	75
5	California	58
6	Colorado	63
7	Connecticut	8
8	Delaware	3
9	District of Columbia	1
10	Florida	67
11	Georgia	159
12	Hawaii	6
13	Idaho	44
14	Illinois	102
15	Indiana	92

16	Iowa	99
17	Kansas	105
18	Kentucky	120
19	Louisiana	64
20	Maine	16
21	Maryland	24
22	Massachusetts	14
23	Michigan	83
24	Minnesota	87
25	Mississippi	82
26	Missouri	115
27	Montana	57
28	Nebraska	93
29	Nevada	17
30	New Hampshire	10
31	New Jersey	21
32	New Mexico	33
33	New York	62
34	North Carolina	100
35	North Dakota	53
36	Ohio	88
37	Oklahoma	77
38	Oregon	36
39	Pennsylvania	67
40	Rhode Island	5
41	South Carolina	47
42	South Dakota	66
43	Tennessee	95
44	Texas	254
45	Utah	29
46	Vermont	14
47	Virginia	136
48	Washington	39
49	West Virginia	55
50	Wisconsin	72
51	Wyoming	23
TOTAL		**3,143**
TOTAL DATA POINTS		**40,833**

Figure 1

Spaghetti Plot (All Data)

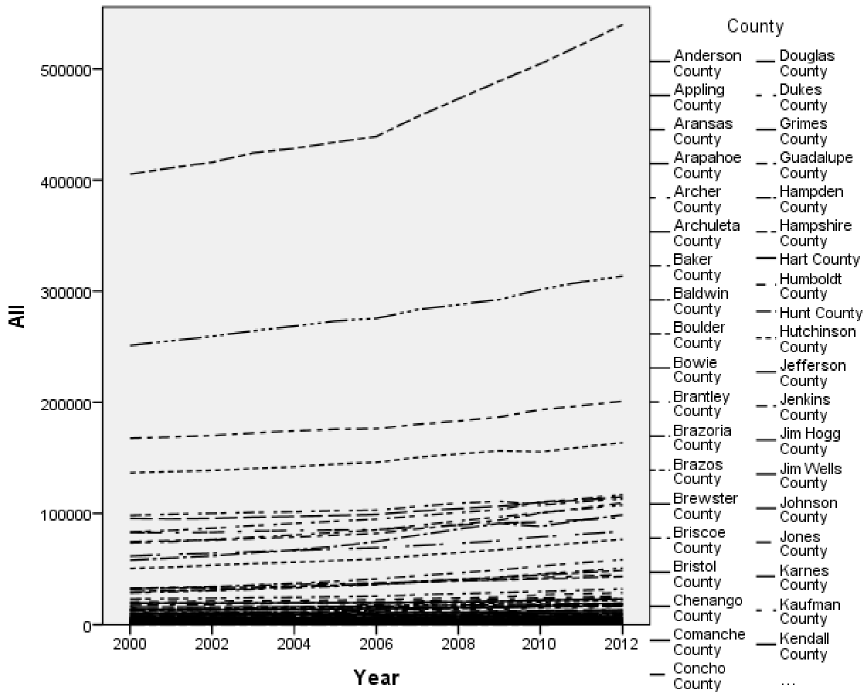


Figure 2

Spaghetti Plot (Hispanic Data)

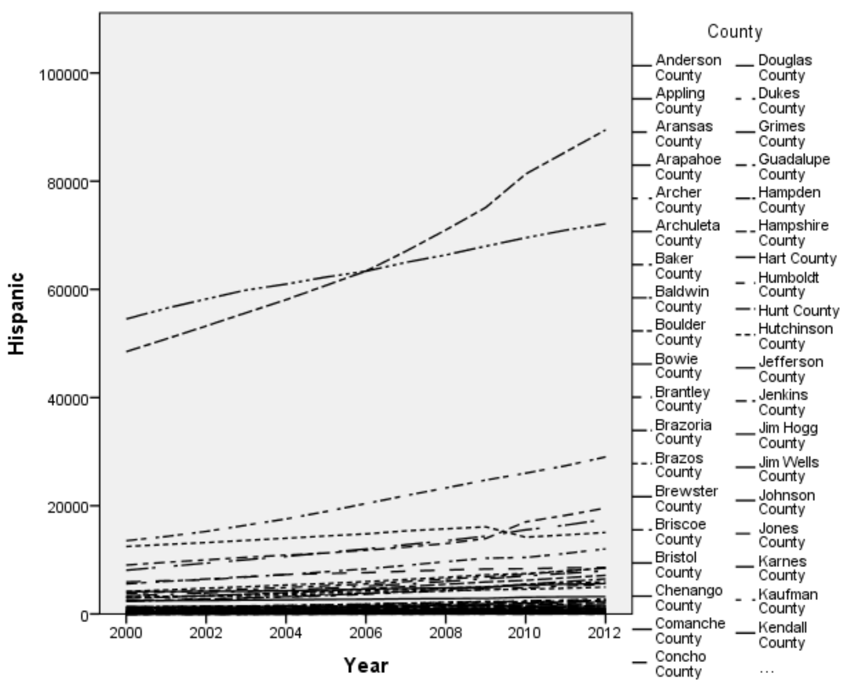


Table 2a

Descriptive Statistics (All Data)

Year	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Y2000	3143	15	1237488	14613.17	42891.31	1839664409.91
Y2003	3143	16	1300362	15279.39	44575.84	1987005589.31
Y2006	3143	12	1348348	16082.06	46311.38	2144743588.10
Y2009	3143	9	1466821	17620.91	50418.24	2541998841.03
Y2012	3143	13	1628440	19395.18	55348.08	3063410264.95

Table 2b

Descriptive Statistics (Hispanic Data)

Year	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Y2000	3143	0	272001	800.59	7612.83	57955131.88
Y2003	3143	0	310567	928.10	8536.57	72873033.70
Y2006	3143	0	347075	1081.93	9503.92	90324545.37
Y2009	3143	0	399645	1283.86	10823.35	117144951.22
Y2012	3143	0	465074	1492.20	12307.38	151471485.87

Table 3a

Comparative Table (All Data)

Model	Details	Fixed	NPar	Chi-Square	df	p	NFI	CFI	RMSEA	Chi-Sq/DF	Chi-Sq Diff Test
M3	Three-Factor Polynomial LGM (with all quadratic loadings fixed)	Error Means to 0, Error Variances to 0, Factor Means to 0	14	3210.56	6	.000	.965	.965	.412	535.09	Sig.
M2	Two-Factor Unspecified LGM (with last 1 slope loading free to estimate)	Error Means to 0, Error Variances to e (e4 set to 0),	9	10974.20	11	.000	.880	.880	.563	997.66	Sig.

M1	Two-Factor Unspecified LGM	Factor Means to 0 Error Means to 0, Error Variances to e (e2, e4 set to 0), Factor Means to 0	8	12504.70	12	.000	.863	.863	.576	1042.06	NA

Table 3b

Comparative Table (Hispanic Data)

Model	**Details**	**Fixed**	**NPar**	**Chi-Square**	**df**	**p**	**NFI**	**CFI**	**RMSEA**	**Chi-Sq/DF**	**Chi-Sq Diff Test**
M3	Three-Factor Polynomial LGM (with all quadratic loadings fixed)	Error Means to 0, Error Variances to 0, Factor Means to 0, Latent Variable Error Variance to e (e1, e3 set to 0)	12	4523.51	8	.000	.953	.953	.424	565.44	Non-sig.
M2	Two-Factor Unspecified LGM (with last 3 slope loadings free to estimate)	Error Means to 0, Error Variances to e (e1, e3 set to 0), Factor Means to 0	11	3553.94	9	.000	.963	.963	.354	394.88	Sig.
M1	Two-Factor Unspecified LGM	Error Means to 0, Error Variances to e (e1, e3 set to 0), Factor	8	14920.29	12	.000	.844	.844	.629	1243.36	NA

	Means to 0

Figure 3

Two-Factor Unspecified LGM With 1 Freely Estimated Loading (All Data)

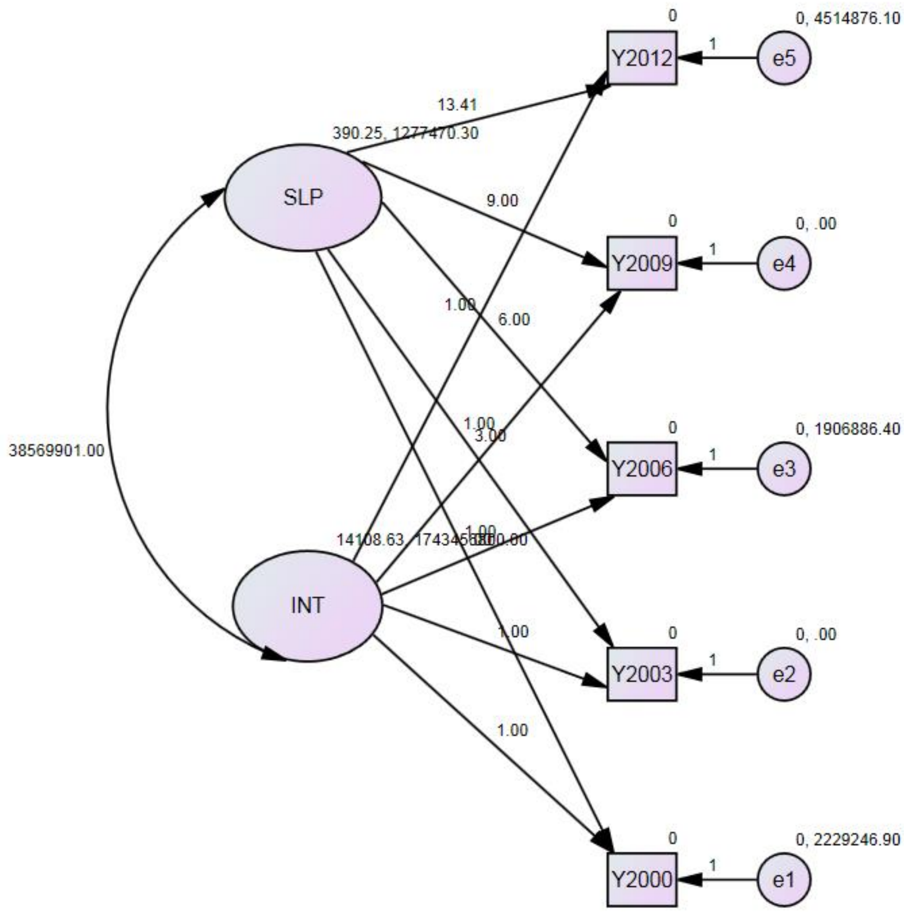
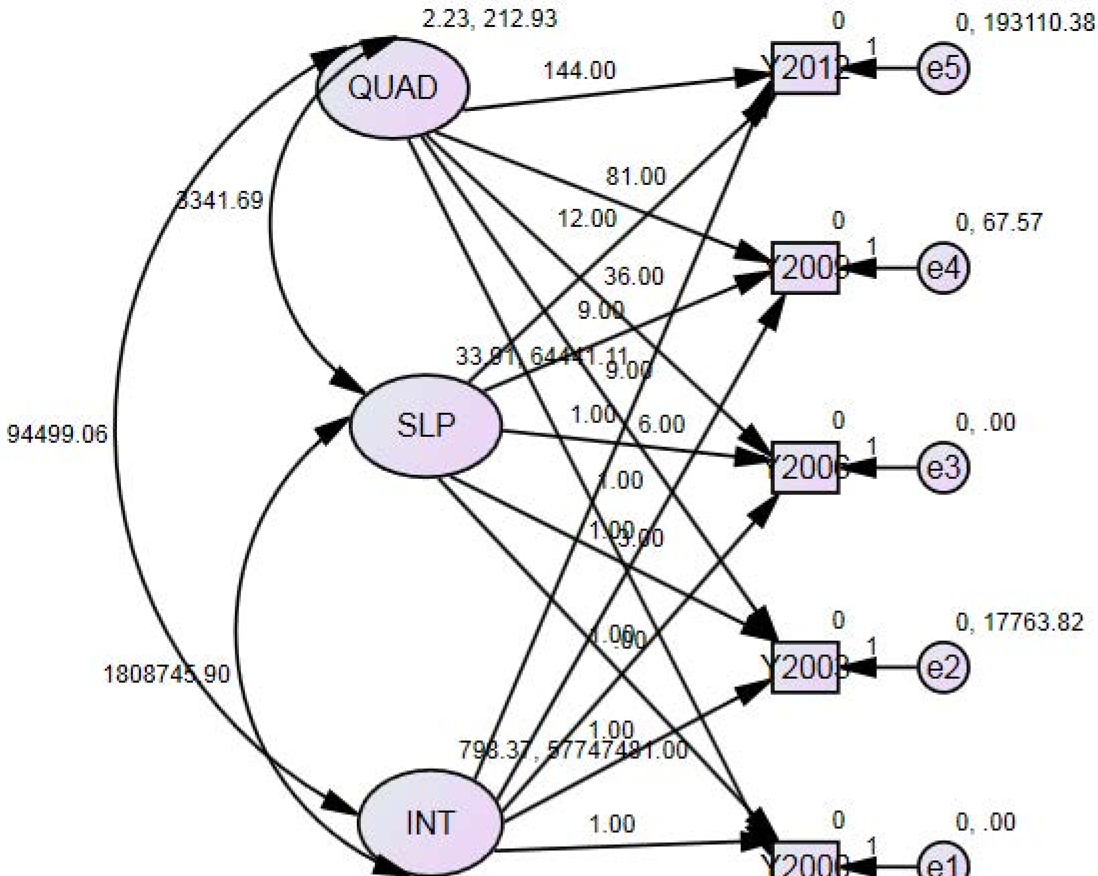


Figure 4

Three-Factor Polynomial LGM With All Quadratic Loadings Fixed (Hispanic Data)


2.23, 212.93
QUAD
144.00
0
Y2012
1
e5
0, 193110.38
81.00
3341.69
12.00
0
Y2009
1
e4
0, 67.57
36.00
9.00
33.91, 64441.11
9.00
SLP
94499.06
1.00
6.00
0
Y2006
1
e3
0, .00
1.00
1.00
3.00
0
Y2003
1
e2
0, 17763.82
1.00
.00
1808745.90
1.00
798.37, 57747481.00
INT
1.00
0
Y2000
1
e1
0, .00