Location, Location, Location:

An Econometric Analysis of Restaurant Location Selection

in Connecticut, Maryland and New Jersey.

Abstract: Site selection is paramount in the restaurant industry for the success and viability of any restaurant. This paper will analyze 2000 and 2008 data at the county level for the states of Connecticut, Maryland and New Jersey to explain variations in the total number of restaurants by county. A change regression is also analyzed to determine how changes in the selected variables effect changes in the number of restaurants in the selected counties. These three states are chosen since they are all eastern coastal states with a high population density. The factors that affect restaurant numbers and growth are concluded to be a high local population, low female labor force participation rates, low population density figures, a high local per capita income and whether the county holds major vacation/tourist destinations. The study finds that in New Jersey, the best counties for new restaurant development are Hunterdon, Somerset and Ocean counties. In Maryland, the best counties for future development are Calvert and Talbot counties. Lastly, in Connecticut, all counties are already oversaturated with full service restaurant competition and therefore, Connecticut should be avoided in future full service restaurant development. The study also concludes that changes in poverty rates and per capita income have the greatest impact on the changes in the number of full service restaurants in the selected counties.

Pawel Talaga
ECO 495
The College of New Jersey
Advisor: D. Vandegrift
December 23, 2010

Introduction:

The mantra in the restaurant business has always been "location, location, location." With advances in computing and statistics, many potential restaurant owners and franchise corporations now use data mining and statistical analysis programs to determine which locations will be the most successful and profitable. Furthermore, an increasing number of firms have developed software that uses statistical analysis of local population density, household incomes and even the number of cars passing by per day to determine whether a potential restaurant location will be successful. Accordingly, we expect that restaurant densities will vary with income, percentage of two earner households, population densities and whether the area attracts a significant number of tourists.

This paper will analyze data at the county level for the states of Connecticut, Maryland and New Jersey to explain variations in restaurant densities. These three states are chosen since they are all eastern coastal states with a high population density. We expect that our analysis will complement site-specific analyses for specific locations within the county since the model explains where the market for prepared meals may be saturated at the county level.

We use county population, population density, per capita income, female labor force participation rate, percentage of housing units that are seasonal, and poverty rates to establish which Connecticut, Maryland and New Jersey counties are underserved by full-service food and drinking establishments. Data from 2000 and 2008 from the Bureau of Economic Analysis (BEA) and Census Bureau are used in a regression analysis to determine whether predicted values of the number of full service food and drinking establishments differ from the actual values in a particular county. Eight counties are selected from each state with the greatest difference in actual versus predicted values in full service restaurants, four with lower than predicted and four with higher than predicted. The findings are also compared to percentage changes from 2000 to 2008 in full service food and drinking establishments for these eight counties in each state to determine if franchises and independent restaurant owners have been following the site selection trends shown by the study. Lastly, we examine how changes in the variables selected impact changes in the number of restaurants. While the study leads to a broad overview of potentially successful food and drink establishments by county, it cannot determine the success of a specific location based site selection decisions because specific street locations, zip codes, or municipalities also determine location success.

Literature Review:

Until relatively recently, restaurant site selection was an ad hoc process. Rogers (1987) reports that “many if not most locations were chosen on the basis of gut-feel, obscure rules of thumb or, if it was a really important decision, by means of licking a finger and holding it up to the wind.” However, these methods have drastically changed with the advent of computer technology into a much more sophisticated decision making process. “Retailers now have access to relatively low-cost decision support technologies and associated retail demand and supply data” (Hernandez & Biasiotto, 2001). Some of these new sophisticated decision support technologies include regressions, computer modeling, data mining as well as various computer related software and services.

Prewitt (2007) and White (2008) explain that restaurant owners and developers use many forms of data analysis including statistical modeling, sales forecasting and customer segment analysis before decisions are made to open in a particular location. Much of the data gathered is based on US Census Bureau data which is used to "decipher the demographic characteristics of a given ZIP code along with information about a trade area's businesses" (Prewitt, 2007). Furthermore, additional tools are used in site selection such as focus groups, credit card data, website questionnaires and blogs to decide on new markets for restaurant locations. White (2008) claims that for restaurant success, a significant amount of research is required, sometimes involving entire teams of experts who examine local demographics, accessibility, traffic counts, visibility and parking. In addition to this research and data collection, White (2008) emphasizes that fair lease agreements and proper financial backing are crucial to both the location decision and the ultimate success of the eatery.

Using data gathered from multiple sources, Spencer (2007) creates the "Restaurant Growth Index (RGI)." The RGI uses a formula to identify restaurant spending per capita in 363 metropolitan areas based on data from the U.S. Census Bureau's 2002 Census of Retail Trade. The RGI score is calculated based on an area's total restaurant sales and restaurant sales as a percentage of per capita income, compared to the nation as a whole. The formula reveals that many of the best metropolitan areas to open a restaurant are vacation destinations and cities with colleges and universities. In New Jersey, the top rankings include Atlantic City and Ocean City which are both tourist destinations and the Trenton-Ewing area which has multiple colleges and universities in the surrounding area. In Connecticut, the RGI scores are highest for New London, Norwich, and Bridgeport, which are densely populated areas with many other businesses and attraction destinations. Lastly, in Maryland, RGI scores are highest in Cumberland, Baltimore and areas near Washington DC which are all areas that are densely populated with students and visitors.

Katz (2006) explains that one key factor in restaurant success is the development of a customer profile unique to a restaurant concept which deciphers the type of clientele that would frequent the restaurant. Following the creation of the customer profile, the developer or owner must select an ideal-site model for the restaurant using demographic figures and geographic variables. By using the customer profile and ideal site model, a color-coded map is created to identify “the geographic clusters where a high percentage of the defined customers are found” (Katz, 2006). Lastly, the restaurateur must evaluate the specific restaurant locations to determine if they meet the criteria set from the previous two steps. Using these steps, Katz explains that an effective population base index is created to represent precise sales projections for restaurant sites. This index is used by both chains and independent operators in site selection as well as by franchisors in the decision to grant or reject a proposed franchise in a specific location.

Technological advances in the site selection process have also reduced the role of real estate brokers in the location decision process (Egan, 2007). The brokers now take a back seat to software since “site selection technology has become as important as local real estate brokers” (Egan, 2007). Data and technological techniques now allow potential restaurant owners and developers to gain knowledge of new markets and give owners the ability to tailor this knowledge into a successful restaurant concept and location much faster than the old system. Furthermore, site selection technologies and firms are unbiased compared to an assessment from a broker whose primary interest is in selling or leasing property (Egan, 2007). Egan (2007) explains that eventually satellite images will be used to analyze specific locations. With an increasing number of site-selection technology companies competing in the business, they will develop even more detailed information about household spending for different demographics and geographic locations.

Technological developments have caused an evolution away from old methods towards more detailed location decision making rules. Holaday (2007) claims that the old mantra "location, location, location" has to be replaced in the current marketplace. Instead, in keeping up with today's ever evolving and fast paced economic environment, the new saying for success in the restaurant industry should be "location, the right concept and the right sales-to-investment ratio." The increasing complexity of consumer demands needs to be constantly assessed and reassessed to achieve success. Furthermore, restaurants must evolve with these changes in demand to remain profitable. Both chain restaurants and independent operators are using technology such as online site-selection services and demographics databases to scout locations before the decision to invest is made. By using technology, restaurateurs and investors "are adjusting their strategies, and taking a more critical view of site opportunities than in the past" (Holaday, 2007).

Pittman (2006) examines site selection on the basis of risk aversion stating that most businesses are risk averse when they make location decisions. To evaluate competing locations, prospective restaurateurs determine push and pull factors of specific locations. Pittman (2006) explains that "push factors include unfavorable local business climate or obsolescence of existing facilities. Pull factors include the development of new markets or demographic shifts." These factors are used along with risk analysis to determine which locations will be successful.

Although many companies are already using statistical modeling and regression to determine potential location success, many of their methods are not divulged to the public and competitors. Therefore, a gap in literature exists as to which economic factors and indicators have the greatest effect on restaurant success and viability. This study exposes which factors have the most significant relationship to the number of restaurants in a county and these results are likely to match specific municipality location decisions. The study also determines which counties in Connecticut, Maryland and New Jersey have room for restaurant development and which counties are oversaturated with competition.

Data and Methods:

To investigate the determinants of restaurant density, we collect county-level data for 2000 and 2008 data from the Bureau of Economic Analysis (BEA) and Census Bureau for the number of full service food and drink establishments, population, population density, per capita income, female labor force participation rates, seasonal housing unit rates, and poverty rates. The analysis aims to predict the number of full service food and drinking establishments in the New Jersey, Maryland and Connecticut counties and compare the predicted values to the actual values. Eight counties are then chosen from each state which have the largest disparity from the predicted values, four with lower than predicted values and four with higher than predicted values.

We also analyze percentage changes from 2000 to 2008 in full service food and drinking establishments in the eight chosen counties with the greatest disparity to determine if franchisors and independent restaurant owners have been following the location trends shown by the study. The predicted versus actual number comparisons are used in conjunction with percent increases in food and drinking establishments to determine whether the study's findings are accurate and already used in site selection decisions.

County population is likely to show a positive impact on the number of restaurants. If propensity to eat at a restaurant is the same across counties, a larger population will support more restaurants. We further expect that more densely populated counties will tend to hold more food and drinking establishments because the driving distance to a given establishment will be lower when population density is higher. Therefore, with lower time costs, we expect more consumption of restaurant meals. Howver, more densely populated areas are likely to have higher land and liquor license prices which may negatively correlate to the total number of restaurants in a county. Permanent customers that live near the restaurant are a key source of restaurant success and therefore, population density is one of the most significant deciding factors in site selection.

We expect that the number of restaurants will be positively associated with per capita income because, in areas with larger incomes, people spend more money on personal consumption and therefore, local businesses are more successful. Both retail and wholesale industries base their location decisions on the local per capita income and median household income of the surrounding area. The restaurant industry is especially affected by this variable because individuals and households with larger incomes can afford to dine out instead of saving money by cooking at home.

The effect of female labor force participation on the number of restaurants is indeterminate. With a rise in female labor force participation rates, women no longer stay at home to cook, clean and care for children. Instead, many women are now just as busy as men with work and career advancement which leaves little time to cook and clean up the mess associated with cooking a meal at home. Instead, busy families with multiple earners are more likely to frequent restaurants to save time and frustration. The rise in female labor force participation rates throughout recent history also serve to show the rising demand for eateries as more and more people decide to dine out instead of cooking meals at home. However, it is also possible that dual earner households are more reliant on both incomes and that one income is not enough to sustain a household or family. Therefore, this variable can have either a positive or negative correlation with the total number of restaurants in a county. For this variable, the 2000 figures are based on 3 year estimates (2000-2002) and 2008 figures are based on 5 year estimates (2005-2009).

It is also likely that counties with vacation and attraction destinations are attractive counties to open a restaurant. Eight of the top ten scoring markets for restaurant growth and success based on the Nielsen Company's Restaurant Growth Index (RGI) prove to be vacation destinations. Therefore, vacation and attraction destinations are used based on 2000 Census for the percentage of seasonal or vacation homes in a county. When people are away on vacation, they often do not have the convenience of a stove or a refrigerator stocked with food items as they do in their homes. Instead, vacationers often eat out for every meal of the day which is a certain economic boost to restaurant success.

Poverty rates, or the percentage of county population living in poverty, are also likely to have an effect on the number of full-service restaurants. Areas with a large percentage of the population living in poverty are likely to have a propensity to have a low number of full-service food and drink establishments because the local population cannot afford to dine and drink out. People living in poverty often use government assistance such as welfare and food stamps to purchase food and have little or no money to spare on food that is prepared for them or high priced alcoholic and non-alcoholic beverages. However, high poverty rates may imply large pools of unskilled workers and restaurants typically hire large numbers of unskilled workers. As such, restaurants in areas with higher poverty rates may have lower costs.

Results:

Tables 1.1 and 1.2 report descriptive statistics of the data. The mean number of restaurants for the 53 selected counties in the year 2000 is 220.49 restaurants with a standard deviation of 200.54 and these figures are higher in 2008. In, 2000, the minimum number of restaurants in a county is 11 and the county with the most restaurants has 759. There are many variations in the data throughout both selected years that must be explained. The variations in the values in the number of restaurants are explained by the multiple regression results which are corrected for heteroskedasticity.

Table 2 reports the results of the regression for the predicted number of full-service restaurants. 2000 data is analyzed since it is very similar to 2008 data. An analysis of the results finds that population, percentage of seasonal units and per capita incomes have the most significant relationship to the amount of restaurants in a county. In 2000, each additional person in a county's population adds a fractional value of 0.000651 restaurants. Therefore, dividing 1 restaurant by 0.000651, we find that it takes an average increase of 1,536 people in a county population for a 1 unit increase in the number of restaurants in a county. Per capita income has a positively correlated parameter estimate of 0.007 meaning that a $142.86 increase in annual county per capita income increases the average number of restaurants in a county by one.

Surprisingly, neither population density based on people per square mile nor the poverty rate has any effect on the number of restaurants within a county for either year. However, female labor force participation rates are also negatively correlated to the number of restaurants in a county in both selected years. Therefore, in 2000, for each 1% increase in female labor force participation rate, there are 5.85 less restaurants in the county. This is surprising since dual earner households are likely to have higher total incomes and more money to spend on food and drinks at restaurants. Instead, higher female labor force participation rates appear to drive down the average number of restaurants per county. The reason for this may stem from the fact that dual earner households are likely more reliant on both incomes and do not have much money to spare on restaurant food and drinks.

Poverty rates are positively correlated with the number of restaurants in a county in 2000 but are negatively correlated in 2008. For 2000, a value of 1.98 means that for each 1% increase in county poverty rate, there is an average of 1.98 more restaurants in a county. This is surprising since county poverty rates were hypothesized to negatively correlate with the total number of restaurants in a county. In 2008, the sign becomes negative which was expected. This variable however is not highly significant.

The percentage of seasonal homes variable is positively correlated in both selected years with the number of restaurants in a county. The 2000 parameter estimate for this variable is 1.29. This means for each percentage point increase in percent of homes as seasonal or vacation homes equates to the county having an average of 1.29 more restaurants. This was expected since vacationers are more likely to eat out and there are typically more restaurants in vacation destinations.

Table 3 reports a regression that analyzes the effect of changes in each of the variables over the period 2000-2008. The results of this regression show how changes in variables effect the change in the number of restaurants as well as which changes in the variables are most significant to changes in the number of restaurants. The change regression results show that changes in the poverty rate and changes in per capita income have the greatest impact on the change in the number of restaurants in the selected counties. However, both of these results are surprising since the “Change in Poverty” variable is positively correlated with change in the number of restaurants while the "Change in Per Capita Income" variable is negatively correlated. This may be caused by restaurants locating in areas where there are cheaper sources of labor as well as lower land, property tax and liquor license costs. Counties with a higher per capita income and a lower poverty rate have scarce cheap labor and land costs are typically higher. Therefore, restaurants appear to be moving into areas with cheap labor and low land and property tax costs.

Perhaps the most important implication of the study is the difference between actual and predicted values of the number of restaurants in the counties studied. Table 4 reports on differences between predicted and actual values for key New Jersey counties. Counties with a significantly higher number of predicted restaurants versus actual restaurants will likely be a good place to open a full-service restaurant. Conversely, counties with actual numbers that are higher than predicted values are likely to be oversaturated with competition and are therefore not great places to open future restaurants. 2000 figures are analyzed to see which counties are determined to be underserved and which counties are oversaturated with full service restaurants. The figures are then compared to 2008 data to determine if restaurants owners have been following the trends shown by the study. The figures are then analyzed again to determine if further growth is necessary beyond the 2008 number of restaurants. The counties that remain below the 2000 predicted values in 2008 are determined to still have room for further restaurant growth and development.

While many NJ counties have estimated values that are close to the actual values, there are a few outliers. Most New Jersey counties had an increase in the number of restaurants between 2000 and 2008 but the few that experienced a decrease between these years have a predicted number of restaurants lower than actual numbers of restaurants based on 2000 data.

Both Atlantic and Bergen County are oversaturated with restaurant competition. However, both counties have still seen growth between 2000 and 2008. This may be because these two counties are both major tourist destinations with relatively few seasonal homes. Bergen County hosted major sports franchises such as the NY Giants, NY Jets, NJ Nets and NJ Devils from 2000 to 2008. Also, Atlantic County is home to Atlantic City which is a major gambling and tourist destination. Cape May and Morris Counties were both also found to be oversaturated with competition. Not surprisingly, our results show that many restaurant owners and franchisors have been pulling out of these counties as seen by the negative percent changes in the total number of full service restaurants between 2000 and 2008.

Essex, Hunterdon, Ocean and Somerset counties were shown to be the most underserved counties in New Jersey based on the study results. These four counties had the greatest disparity between actual and predicted values in 2000. Restaurant owners and developers have also likely noticed this, as seen by the positive percent change rates in the number of restaurants in all of these counties. Furthermore, as of 2008, none of the 2008 figures have caught up to the 2000 predicted values and therefore all of these counties are shown to have further room for restaurant development. Thus, the New Jersey counties with the greatest potential for growth are determined to be Hunterdon, Somerset and Ocean counties.

Like New Jersey, most Maryland counties have showed increases between the years 2000 and 2008 in the total number of full service restaurants in each county. Table 5 reports on differences between predicted and actual values for key Maryland counties. The few counties that showed decreases were found to have predicted values based on the study that were less than the actual number of restaurants in the county. Although Frederick and Washington counties in Maryland appeared to be oversaturated by the study, they still had increases in the number of full service restaurants between 2000 and 2008. The four most underserved counties in 2000 were Anne Arundel, Calvert, Howard and Talbot. Of these counties, the 2008 figure have nearly caught up to 2000 predicted values for Anne Arundel and Howard counties. Therefore, the Maryland counties that are shown to have the highest potential for growth appear to be Calvert and Talbot counties.

While both New Jersey and Maryland have both positive and negative residuals based on the regression equation, Connecticut predicted values were consistently lower than actual values throughout all eight Connecticut counties. In Connecticut, all eight counties have a predicted value that is lower than the actual number of restaurants in 2000. Furthermore, all eight counties showed increases in the number of full service restaurants between 2000 and 2008. This shows that the state of Connecticut is likely already oversaturated with restaurant competition and is therefore not an ideal state to start a restaurant at the current time. However, the least oversaturated with full service restaurant competition counties appear to be New London and Tolland counties.

Conclusion:

Restaurant site selection has evolved throughout recent history because of technological advances in the fields of statistics and data mining. Statistical and computer software is now used to determine which factors play into restaurant viability and success. The decision of where to locate is paramount to the future success of a full service restaurant. A good location will increase profits and success, while a bad location will likely lead to losses and restaurant failure. By studying the data of local populations, restaurant owners, developers and franchisors can make decision that will lead to a profitable business.

The study reveals that some counties are already oversaturated with competition while other counties appear to be underserved. Many of the counties that the study found to be oversaturated with restaurants had decreases in the total number of restaurants between 2000 and 2008. However, the underserved counties have room for growth in the restaurant industry and should therefore be considered when planning a potential restaurant in the future. The factors that affect restaurant numbers and growth are concluded to be a high local population, lower female labor force participation rates, lower land and liquor license prices (as shown by lower population density figures), a higher local per capita income and whether the county holds major seasonal units for vacationers. County poverty rates are found to have a lesser impact on the number of restaurants in a given county. Using this data, it is concluded that in New Jersey, the best counties for new restaurant development are Hunterdon, Somerset and Ocean counties. In Maryland, counties with the highest room for growth in the number of restaurants are Calvert and Talbot counties. Lastly, in Connecticut, all counties are already oversaturated with full service restaurant competition and therefore, Connecticut should be avoided in future full service restaurant development. Additionally, the study finds that changes in poverty rates and per capita income have the greatest impact on the changes in the number of full service restaurants in the selected counties.

Works Cited

Egan, John (2007). “Site Selection: The Secret Sauce.” *National Real Estate Investor*. 49(5): 49-51.

Hernandez, Tony and Biasiotto, Marco (2001).”Retail Location Decision Making and Store Portfolio Management.” *Canadian Journal of Regional Science.*24(3): 399+.

Holaday, Susan (2007). “Insights in Sight Selection.” *Nation’s Restaurant News*. 41(5): 92.

Katz, Mark (2006). “You Do The Math: Site Selection Has Big Sales Potential.” *Nation’s Restaurant News.* 40(15): 40-41.

Pittman, Robert H. (2006). “Location, Location, Location: Winning Site Selection Proposals.” *Management Quarterly*. 47(1): 12+.

Prewitt, Milford (2007). “Customer Data Mining Aids in Quests for Lucrative New Sites” *Nation’s Restaurant News*. 41(18): 1-2.

Rogers, D. 1987. "Shop Location Analysis" , in E. McFayden (ed.), The Changing Face of British Retailing. London: Newman Books.

Spencer, Tom (2007). “The Best Places to Open Your New Restaurant.” *Restaurant Business.* November 2007: 20-45.

U.S. Census Bureau Data. Retrieved November 2, 2010, from: http://quickfacts.census.gov

U.S. Bureau of Economic Analysis Data. Retrieved November 23, 2010, from: http://www.bea.gov/

White, Geneva (2008). “Location, Location, Location” *Nation’s Restaurant News.* 41(27): 10-11.

Table 1.1: 2000 Characteristics of Counties

Variable	Obs	Mean	Std. Dev.	Min	Max
Restaurants 2000	53	220.4906	200.5375	11	759
Population_2000	53	328913.4	290382.8	19491	906145
Pop.density2000	53	1237.509	1990.623	46	10000
FLPR 2000-02	53	61.86792	4.090504	50	70
poverty_2000	53	8.396226	4.011232	3	23
PerCapInc 2000	53	24983.06	5562.604	15965	38350
%2ndhomes2000	53	27.01887	22.23692	3	88

Table 1.2: 2008 Characteristics of Counties

Variable	Obs	Mean	Std. Dev.	Min	Max
Restaurants 2008	53	240.7547	221.0752	11	879
Population_2008	53	336320.5	292286.0	20269	953685
Pop.density2008	53	1245.774	1950.812	46	9739
FLFPR 2005-09	53	61.69811	3.954476	52	71
poverty_2008	53	8.981131	4.069070	4	23
PerCapInc 2008	53	32024.04	8948.178	19332	51080
%2ndhomes2008	53	24.96226	22.24078	2	86

Table 2. 2000 and 2008 Data: Regression Coefficients and t-values

Variable	2000 Parameter Estimate (Standard Error)	2008 Parameter Estimate (Standard Error)	2000 t Value (2008)	2000 Pr > t (2008)
Constant	150.23 (284.1)	350.93 (342.5)	0.53 (1.02)	0.60 (0.311)
Population	0.000651*** (0.0000706)	0.00074*** (0.000086)	9.22 (8.66)	<0.0001 (<0.0001)
Population Density	-0.0057 (0.0072)	-0.0065 (0.0090)	-0.79 (-0.73)	0.44 (0.47)
Female LFPR	-5.85* (3.85)	-8.30* (5.02)	-1.52 (-1.65)	0.14 (0.11)
Poverty Rate	1.98 (4.75)	-.30 (4.49)	0.42 (-.07)	0.68 (0.95)
Per Capita Income	0.0070** (0.0029)	0.0040** (0.0015)	2.40 (2.65)	0.021 (0.011)
% of Seasonal/ Vacation Homes	1.29*** (0.376)	1.39*** (0.49)	3.43 (2.83)	0.001 (.007)

Dependent variable: Number of restaurants in a county
Robust standard errors in parentheses.
# of Observations: 53
*** = significant at 0.01.
** = significant at 0.05.
* = significant at 0.15.

Table 3: Change Regression Results:

Change_Restaurants	Coeff.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
Change_Pop. *	.7963215	.5673254	1.40	0.167	-.34499	1.937633
Change_FLFPR	1.107636	1.028768	1.08	0.287	-.9619782	3.17725
Change_Poverty**	.1867428	.1006533	1.86	0.070	-.0157455	.3892311
Chng_PerCapInc***	-.035227	.0169093	-2.08	0.043	-.0692442	-.0012098
Change_%2nd homes	-.0237756	.062149	-0.38	0.704	-.1488033	.101252
_Cons	5.486702	3.592352	1.53	0.133	-1.740178	12.71358

# of Observations: 53
*** = significant at 0.05.
** = significant at 0.10.
* = significant at 0.20.

Table 4. Predicted vs. Actual Values, Residuals and Changes From 2000-2008

New Jersey

Underserved or Oversaturated by Study Findings	County	Predicted	Actual	Residual	% Change 2000-2008
Oversaturated	**Atlantic**	205	255	50	+24.3%
Oversaturated	**Bergen**	624	738	114	+1.8%
Oversaturated	**Cape May**	194	285	91	-11.3%
Oversaturated	**Morris**	387	436	45	-5.6%
Underserved	**Essex**	485	418	-67	+6.9%
Underserved	**Hunterdon**	155	95	-60	+21.1%
Underserved	**Ocean**	456	364	-92	+4.4%
Underserved	**Somerset**	275	222	-52	+15.3

Table 5. Predicted vs. Actual Values, Residuals and Changes From 2000-2008

Maryland

Underserved or Oversaturated by Study Findings	**County**	**Predicted**	**Actual**	**Residual**	**% Change 2000-2008**
Oversaturated	**Cecil**	47	55	8	-7.8%
Oversaturated	**Wicomico**	16	60	44	-7.1%
Oversaturated	**Frederick**	63	136	73	+3.7%
Oversaturated	**Washington**	50	86	36	+9.3%
Underserved	**Anne Arundel**	324	278	-46	+14.4%
Underserved	**Calvert**	73	42	-31	+33.3%
Underserved	**Howard**	164	132	-32	+23.5%
Underserved	**Talbot**	120	46	-74	+13.0%