# Something old, something new: MBA program evaluation using shift-share analysis and Google Trends

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## ABSTRACT

Shift-share analysis is a decomposition technique that is commonly used to measure attributes of regional change. In this method, regional change is decomposed into its relevant functional and competitive parts. This paper introduces traditional shift-share method and its extensions with examples of its applicability and usefulness for program evaluation and development, strategic planning, enrollment management and other traditional functions of higher education administration. To illustrate we provide an appraisal of the impact of demographic and employment changes resulting from the great recession on the MBA program of a regional private university in the state of Connecticut. We establish the validity of our shift-share based analysis with a Google Trends examination of relevant keywords.

Keywords: shift-share, strategic analysis, enrollment management, Google trends, MBA program management, graduate program planning and development



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*Rodriguez is corresponding author. We thank L. Christie Boronico, Lesley DeNardis and Sridhar Srinivasan for helpful comments.

## INTRODUCTION

Strategic decision-making in higher education planning, enrollment management, and program development among other higher education administrative activities routinely rely on qualitative and quantitative metrics and instruments. These may include all or some of financial performance metrics, labor-force skills-needs-surveys, balance-scorecard approaches, SWOT analysis, comparisons to hand-picked benchmarks and comparables, appraisals of changing generational shifts in student character, and national, regional and state economic and demographic analytics (Papenhausen & Einstein, 2006; Chen, Yang, & Shiau, 2006; McDevitt, Giapponi, & Solomon, 2008; Wells & Wells, 2011). Lately, it is possible to add data mining processes, Google trends analysis and other online-based tools (Choi & Varian, 2009; Goel, Hofman, Lahaie, Pennock, & Watts, 2010).

Consider adding to this toolkit a technique remarkably enduring and popular in regional economic development analysis and related fields. The sheer volume of current research and professional practice relying on shift-share analysis proves these tools have managed to maintain their relevance for over fifty years (Dunn, 1960). The benefit of shift-share analysis to higher education administration is that it provides a reliable, simple to use, descriptive appraisal of a region's relative performance and its constituent components for any variable examined. For most institutions of higher education, failure to decide strategic direction based on a uniform and robust understanding of the dynamics of local and regional growth and demographic change often ascribes too much discretionality to faddish programs and ad-hoc initiatives.

To illustrate the usefulness of shift-share analysis for higher education decision-making two examples are provided. They are drawn from an actual review and appraisal of an existing MBA program in which shift-share provided a key analytical strength. And although some tentative strategy recommendations drawn from the insight conveyed by the analysis are provided, the primary objective of this paper is advocacy of the recommended techniques, rather than contingent strategy.

Contextually, the case study is set within a small, private, regional university in Connecticut with a full slate of undergraduate programs and professional graduate programs. However, the applicability of shift-share easily analysis extends beyond these particular confines.

The methodology, analysis and results are presented in this paper. The following section provides the setting for the analysis. A description of the recommended technique: shift-share analysis follows. The third section contains an explanation of the technique in the context of employment within industrial sectors – to appraise the performance of local economic sectors and thereby identify the comparatively better-performing ones and those poised to return to growth upon the rebounding of the economy. A second example looks at changing age-cohorts in the state. This complementary view reveals the direction of changes in the size and composition of the traditional age-group of prospective MBA students. Last, to gauge the soundness and robustness of the conclusion of the analysis a Google Trends analysis on MBA programs is conducted. The results of the trend analysis support the inferences drawn from the shift share analysis. The last section concludes.

**THE FRAME**

The study was conducted during the fall of 2012 a few years after the economic downturn known as the great recession – which officially lasted from 2007 through 2009. Several features of the downturn had an especially detrimental impact on demand for the MBA degree in the program's traditional intake region – the greater New Haven region. Typically, applications to MBA programs rise in bad economic times and fall in good times (Edmonston, 2008). Realized increases in graduate school enrollment are generally attributed to the enhanced appeal of education as a result of its declining opportunity cost (Bedard & Herman, 2008). Yet, nearly three full years after the official end of the recession, the Connecticut economy has not entirely recovered in terms of jobs and employment. Moreover, the expected commensurate increase in enrollments failed to materialize during the downturn, contravening the historical countercyclical nature of demand for the MBA degree.

There are plausible region-specific reasons for this decline. Numerous budget-conscious employers across the state trimmed, or entirely eliminated, their continuing-education and tuition-reimbursement monies. The impairment and erosion of considerable wealth held in home-equity as a result of significant declines in residential prices reduced disposable incomes and affected an important avenue of education financing. Typically credit-constrained, the combined economic effects markedly impaired the capacity of potential students to finance their education. Additionally, Connecticut does not appear to be among the favored in the increasing regional job polarization divide, a rift driven by the increasing heft of the "creative" or knowledge economy (Gabe, 2006). And tellingly, as documented later, the state has been experiencing a decline in college-age population growth.

The seeming consequence of these inter-related forces is a reduced demand for the MBA.[1] According to the Graduate Management Admissions Council 65 percent of MBA programs in the Northeastern part of the United States reported a decline (Graduate Management Admissions Council, 2012). Still, notwithstanding current economic events particular to Connecticut, there is evidence that the decline in global demand for graduate business school training commenced long before the current downturn (Lavelle, 2013).

The study offered two salient observations that have a bearing on future enrollment growth and program demand. On the one hand, using Bureau of the Census data it was possible to identify a decline or, at the very least, a paucity of growth of the traditional MBA age-cohort as a result of secular demographic changes in the state. In addition, using BLS employment data by industrial sector allowed the identification of industries that retained some appeal across despite the generalized economic downturn. These areas of strong comparative employment performance reveal a "silver lining" which has the potential to provide a steady demand for trained managers in the near future. Indeed, one can imagine higher education decision-makers

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[1] The Graduate Management Admissions Council (GMAC) administers the Graduate Management Admissions Test (GMAT). Since the GMAT is required for admissions to MBA programs across the world, the number of students sitting for the GMAT in a given year serves as an indicator of demand for the MBA degree. The GMAC noted in their recent report that data collected in 2012 suggested an important change from previous post-recession patterns. "For the past three years of sluggish economic recovery (2009-2011), full-time MBA programs reported slowing or decreasing application growth" (Graduate Management Admissions Council, 2012).

and others charged with strategic planning altering or adapting extant programs to accommodate the reading of the analysis presented here.

**SHIFT-SHARE ANALYSIS**

The problems associated with data-based quantitative studies common in program evaluation and development, are many and varied. Availability, type and quality of data are factors that strongly condition and limit such studies. The more elaborate studies often require a level of sophistication and specialized software often unavailable in most university administrative units.

Shift-share analysis was introduced by E.S. Dunn et al in 1960. It was a method for the determination of the components explaining or decomposing variation in economic variables. As is shown in this paper - its conceptual simplicity can be tapped with any spreadsheet program such as Microsoft Excel running online and freely available data sources.[2]

The conventional shift-share model appraises the performance of one region in relation to a reference one. In this paper New Haven county and Connecticut in the second example are compared to the United States. The MBA program's historical intake region encompasses New Haven county and its immediate surroundings. The analysis looks separately at age-cohorts and employment by sector. The employment analysis is limited to New Haven county whereas the age-cohort analysis encompasses the entire state of Connecticut.

At its most elementary, the analysis entails the casting of a change in a particular economic variable as the sum of three components. Consider the following specification for the decomposition of a change in employment in sector *i* between year 0 and year 1 (the application of the model would be identical for changes in age-cohorts):

$$\Delta E_{i0} = NG_i + IM_i + CS_i$$

Where $\Delta E_{i0}$ is net change in employment in sector *i* in year 0. $NG_i$ is the National Growth component of the realized change in employment in sector *i*. $IM_i$ is the Industry Mix component in sector *i* and $CS_i$ is the Competitive Shift component in sector *i*. The National Growth component $NG_i$ is computed as the product of employment in sector *i* for the beginning year (year 0) times the national growth rate:

$$NG_i = E_{i0}\, x\, (national\ growth\ rate)$$

The National Growth rate component establishes how much employment would have changed in New Haven county had local employment mirrored national growth rates. A calculated positive total across all sectors suggests that New Haven county had faster growing industries; negative value total suggests the opposite – a composition of industry that collectively grew at a slower rate than the national rate. The Industry Mix component $IM_i$ is calculated by multiplying local sector *i* employment in the beginning year (Year 0):

$$IM_i = E_{i0}\, x\, (local\ sector\ i\ growth\ rate) - E_{i0}\, x\, (national\ growth\ rate)$$

[2] In our case we obtained population data from the U.S. Bureau of the Census and employment data from the U.S. Bureau of Labor.

The industry mix component measures the influence of the mix of fast (or slow) growing industries in New Haven county employment compared to that of the nation as a whole net of any nation-wide economic effects.

The Competitive Shift component is computed by multiplying local employment in sector i in the beginning year (year 0), by the difference in the local growth rate in sector i and the national growth rate in sector i:

$$CS_i = E_{i0}\, x\, (local\ sector\ i\ growth\ rate - national\ sector\ i\ growth\ rate)$$

The competitive shift component of local employment change accounts for the gain (or loss) in local employment from an industry growing faster (or slower) that the same industry nationally. This reflects idiosyncratic area conditions that account for the differential performance with industry results at the national level.

After results for all sectors are calculated they are summed to determine the total effect for each component. Thus, the total change in employment is equal to the sum of the sectoral change for each component.

$$\Sigma(E_i) = \Sigma(NG_i) + \Sigma(IM_i) + \Sigma(CS_i)$$

Critics of shift-share analysis point to its static nature. The technique examines change between the initial and final period without considering variation from any intermediate point. It also ignores changes in sectoral structure, competitive intensity, and level of regional employment (Stevens & Moore, 1980). However, immediate interest of this work lies neither in establishing causal factors nor in ascertaining their significance. Rather the focus is on examining existing relative outcomes in employment and age-cohorts – and their relevance to the existing MBA program and proposed program changes.

## Industrial Sector Analysis

Shift-share analysis applied to industrial sectors decomposes changes in employment in a particular sector into three distinct parts, attributable to (1) changes in the national economy; (2) the specific mix of fast or slow-growing industries; and (3) the "competitiveness" of those industries (Lanza, 2004). The focus of the analysis is on New Haven county which encompasses a significant proportion of the MBA student intake area. A region's "share" of a national slump is simply the overall percentage decline in jobs nationally. Any observed difference attributable to industrial "mix" effect is caused by the extent of the difference between Connecticut and the national economy in the sectoral composition of jobs. The balance of observed changes comes from its sectors performing better or worse – i.e. being more or less "competitive" - than the same sectors nationally (Lanza, 2004).

The initial example illustrating the use of shift-share examines changes in employment among 11 major industry categories. The data is obtained from the U.S. Bureau of Labor Statistics' Census of Employment and Wages.[3] The examination period encompasses changes between 2000 and 2011. The data is for New Haven County - identified in the database as FIPS

[3] http://www.bls.gov/cew/home.htm (viewed September 2012)

code 09009. The data extract displayed as indicated in Table 1 (Appendix) show that New Haven county lost over sixty thousand jobs over the period.

The results of the shift-share decomposition are displayed in Table 2 (Appendix). The table contains the tabulation of all realized changes in employment including the competitive or idiosyncratic share component. This latter effect dominates the overall change in New Haven county employment for the period examined. In other words, changes at the local level were of major importance to the region's economy. Specifically, although particular industries account for most of the decline, of the approximately 60 thousand jobs lost practically all can be attributed to idiosyncratic area conditions. Fortuitously, the contribution to employment attributable to the industry mix for the county held the line somewhat (again with varying influence across industries); this can be seen in the column labeled Industrial Mix Component Jobs of Table 2 (Appendix).

Table 3 (in the Appendix) constitutes the "meat" of the analysis. It reveals the areas that did comparatively well – the silver-lining. The idiosyncratic component constitutes the balance of job losses once the national and industry-mix component have been accounted for – what is known as the Expected Jobs Effect. The last column on the right in Table 3 (Appendix)– specifically identifies those areas that performed better than expected; put differently, those areas that "held their own." These better performing sector labels are identified in bold letters. Thus, the relative performance detected suggests potential areas across which to focus marketing or specialized attention from program administrators.

**Changing Demographics and the Aging of Connecticut**

Although programs vary with respect to their preferred student profile – most MBA programs would rather enroll individuals who have some work experience – ideally anywhere between 2-10 years. This implies a target group of individuals between the ages of 24-34 years of age and often into their early forties.

Between 2000 and 2010 Connecticut's population increased by 168,532 individuals, a 4.9 percent increase. However, stark and possibly alarming trends emerge once one takes a look at how the different age cohorts fared relative to each other. Of the net gain in people in the state four out of every five (80 percent) was a senior citizen 65 or older. In fact, practically the entire gain in population over the 10 year period came from those 55 or older; see Table 4 (Appendix).

How did demographic changes in Connecticut compare to changes nationally? In this instance shift-share analysis decomposes changes in age cohorts in Connecticut into three distinct parts, attributable to (1) changes at the national level; (2) the specific mix of fast- or slow-growing groups; and (3) the region's "competitive share (Lanza, 2004)." The latter share reflects the region's ability to capture an increasing portion of a particular age grouping's growth. A positive competitive share indicates that the region has a particular advantage in attracting people in that age grouping relative to the rest of the nation. Similarly, a negative competitive share signals a relative disadvantage.

A region's "share" of a national slump is simply the overall percentage decline in jobs nationally. Any observed difference attributable to industrial "mix" effect is caused by the extent of the difference between Connecticut and the national economy in the sectoral composition of age-cohorts. The balance of observed changes comes from its sectors performing better or worse – i.e. being more or less "competitive" - than the same sectors nationally (Lanza 2004).

For purposes of this analysis, the “pre-adults” group consists of the population under 20, the 20 to 34 year-olds are considered “Young Workers,” “Mid-Career” the 35-54 year olds, “Older Workers” are those between 55-64 years of age, and “Retirees” are age 65 and older. All data is from the Bureau of the Census for the respective years and geographical unit.[4]

A close examination of the two groups of interest for us reveals changes of considerable concern. The Young Workers segment increased at a rate of 1.4 percent. Although positive, the recorded gain is considerably less than the increase of 6.4 percent nationally for the same age group. The Mid-Career workers in the State of Connecticut have fared badly. Whereas nationally this group increased by a tad under 4 percent, we registered a decline of 2 basis points. Figure 1 in the Appendix visually reproduces the data table.

“It is possible – and important - to distinguish the relative influence of national forces from State-wide forces. A shift-share analysis identifies what portion of each group’s change in Connecticut resembles change in the United States – and what portion is unique to Connecticut” (Moor, 2002). “Table 5 (in the Appendix) contains national data on the same age groups”.

Table 6 (Appendix) displays data that -

> nets out the portion of each group’s reported change that is attributable to common national patterns. For example, Connecticut’s Pre-Adult (under 20) population shrank by 9,929 from 2000 to 2010. Had Connecticut mirrored the national average, it would have experienced a net *gain* of 32,143 individuals. Consequently, the Connecticut effect is -42,072 (-9,929 – 32,143 = -42,072) or almost 5 percent of the average size of the group.[5] Connecticut’s birth and death rates do not differ much from national averages net out-migration is the most likely cause of the observed population changes.[6]

These individuals are, for the most part, net out-migrants who left in response to socio-economic conditions that were different in Connecticut than in the US at large.

To summarize: the data – local and state data on both employment and age-cohorts – convey a consistent picture. The lagging effects of the recession in New Haven county have diminished the number of students typically interested in MBA programs. The much desired age-group has dwindled considerably. The employment analysis also reveals those specific industrial sectors that have fared the downturn comparatively better than others.

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4http://www.census.gov (visited 11/07/2013).

5 The average size of the group is obtained by adding up the 2000 and 2010 recorded group population and dividing by two.

6 In 2007, the United States death rate was 803.6 per 100,000 whereas Connecticut’s was 818.1. Source: CDC/NCHS National Vital Statistics System, Mortality. In turn, the United States reported birth rate in 2010 was 13.0 births per 1,000 population (3,999,386 births); Connecticut reported 10.6 births per 1,000 population (37,708). Source: Births: Final Data for 2010, National Vital Statistics Report, Volume 61, No.1 (August 2012). US Department of Health and Human Services, Center for Disease Control & Prevention, National Center for Health Statistics.

## ROBUSTNESS CHECK USING GOOGLE TRENDS DATA

A common exercise in empirical studies is a “robustness check” – whereby a second opinion (in a manner of speaking), is solicited. An independent result via an alternative methodology corroborating and supporting the initial conclusion adds confidence to the original outcome.

The study relied on Google Trends to examine the historical search volume performance of the words MBA & GMAT. The GMAT, or Graduate Management Admission Test, is required by practically all modern MBA programs. Its use serves as an indicator of the interest any one would have on pursuing an MBA degree and enrolling in an MBA program. Similarly, prospective students canvassing the internet for MBA program information will most likely use the word MBA. The search algorithm will flag any search for related phrases or terms. For instance, search volume data for “MBA” will include all searches for “MBA” as well as searches for “MBA UNH,” UCONN MBA,” or “MBA programs. Pursuing an MBA degree and sitting for the GMAT exam are “instances of a natural class of events that represent activities for which it is plausible that individuals might (i) harbor the intention to perform the corresponding action sometime in advance of actually fulfilling it and (ii) signal that intention trough a related web search (Goel, Hofman, Lahaie, Pennock, & Watts, 2010).”

Google Trends provides weekly search volume data for specific terms over a specific time period across specific states or nations. A Google Insights query for a particular term yields data for all searches that contain that specific term. The Google algorithm normalizes the minimum search volume to 0 and the maximum search volume to 100 over the examined time period and within the specified state – Connecticut. The approach consisted of a jointly search for the terms MBA & GMAT over the period from January 2004 till August 2013 for the state of Connecticut.[7] Search volume data retrieved can be seen in figure 2.

What followed was a regression of the natural logarithms of the particular volume index on a time variable. The econometric model is the following:

$$Ln(Volume\ Index) = \alpha + \beta * Time + \varepsilon$$

where $\alpha$ and $\beta$ are the parameters to be estimated and $\varepsilon$ is a random error term. The regression period is limited to the time between January 2004 and October 2012 because data is not available prior to that time. The results are as provided in Table 7 in the Appendix. Both regression results return a negative and statistically significant coefficient on time confirming a secular decline over the same period.

## CONCLUDING COMMENTS

We advocate the use of shift-share analysis as a ready and easily-deployed tool for program performance and program evaluation and development, strategic planning, enrollment management and other traditional functions of higher education administration. To provide an illustration of its flexibility as well as its limitations – this paper reproduces the key points of a

[7] The search terms are the following: http://www.google.com/trends/explore#q=mba%2C%20gmat&geo=US-CT&cmpt=q (August 28, 2013) The August data is partial.

study conducted during the fall semester of 2012. The original review examined the impact of both changing state demographics and regional economic performance on the MBA program offered by a small, private, regional university in the northeast. The results obtained served as basis for a subsequent MBA program review and for general strategic considerations. Several avenues were considered. For example, program administrators considered the plausibility and viability of soliciting and accommodating corporate partnership MBAs so that a particular company could see the value of investing in education directly applicable to their company and their needs. The companies considered were those within the better-performing sectors identified by the analysis.

Program administrators also weighed the creation of multiple or even a series of overlapping, specialized, certificate programs that were to be built upon gradually, to culminate, or to place a student well on their way to a full-fledged MBA. The gradual accretion of certificates would enable a student to make a relatively modest and incremental commitment to continuing education – complete the requirements, appraise the experience, and subsequently consider whether to commit further towards full completion of the program.

These programmatic strategy examples discussed are clearly neither new nor original to this study; numerous MBA programs around the country have adopted them. Obviously, shift-share analysis-cum-google-trends is but one tool. Especially important are appraisals of the impact of rival programs and their competitive responses. Indeed, an understanding of a college's MBA program's relative market positioning is fundamental amidst heightened competition for a declining demographic pool and reduced financing opportunities. However, any such recommendations are less likely to ensure success if deployed in isolation of a deeper understanding of the underlying regional demographics and industrial sensitivity to local economic forces.

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## APPENDIX

**Table 1**

**Employment Changes in Connecticut, 2000 to 2011.**

| Sector | Employment, 2000 | Employment, 2011 | Employment Change | Percent Growth, 2000 - 2011 |
|---|---|---|---|---|
| **Education and Health Services** | 364,550 | 440,666 | 76,116 | 20.9% |
| **Trade, Transportation, and Utilities** | 330,740 | 300,927 | -29,813 | -9.0% |
| **Professional and Business Services** | 217,072 | 199,187 | -17,885 | -8.2% |
| **Manufacturing** | 234,790 | 166,504 | -68,286 | -29.1% |
| **Leisure and Hospitality** | 143,061 | 160,064 | 17,003 | 11.9% |
| **Financial Activities** | 143,440 | 133,998 | -9,442 | -6.6% |
| **Public Administration** | 60,859 | 57,607 | -3,252 | -5.3% |
| **Other Services** | 54,747 | 57,350 | 2,603 | 4.8% |
| **Construction** | 68,372 | 55,616 | -12,756 | -18.7% |
| **Information** | 49,203 | 34,374 | -14,829 | -30.1% |
| **Natural Resources and Mining** | 5,896 | 5,561 | -335 | -5.7% |
| | **1672730** | **1611854** | **-60,876** | -3.6% |

**Table 2**

**Shift-Share Analysis, Connecticut, 2000-2011.**

| Sector | National Growth Component, Percent | National Growth Component, Jobs | Industrial Mix Component, Percent | Industrial Mix Component, Jobs | Competitive Share Component, Percent | Competitive Share Component, Jobs |
|---|---|---|---|---|---|---|
| **Manufacturing** | -0.4% | -939 | -32% | -75,133 | 3.3% | 7,748 |
| **Other Services** | -0.4% | 219 | 6.5% | 3,559 | -1.4% | -766 |
| **Construction** | -0.4% | -273.488 | -17.1% | -11,692 | -1.2% | -820 |
| **Natural Resources and Mining** | -0.4% | -23 | 11.1% | 654 | -16.4% | -967 |
| **Leisure and Hospitality** | -0.4% | -572 | 13.9% | 19,885 | -1.6% | -2,289 |
| **Information** | -0.4% | -197 | -24.6% | -12,104 | -5.1% | -2,509 |
| **Public Administration** | -0.4% | -243 | 5.70% | 3,469 | -10.6% | -6,451 |
| **Financial Activities** | -0.4% | -574 | -1.7% | -2,438 | -4.5% | -6,455 |
| **Education and Health Services** | -0.4% | -1,458 | 23.3% | 84,940 | -2.0% | -7,291 |
| **Trade, Transportation, and Utilities** | -0.4% | -1,323 | -4.1% | -13,560 | -4.6% | -15,214 |
| **Professional and Business Services** | -0.4% | -868 | 4.30% | 9,334 | -12.2% | -26,483 |
| | | **-6,252** | | **6,915** | | **-61,498** |

**Table 3**

**Expected vs. Actual, Connecticut, 2000-2011.**

| Sector | Expected Growth Jobs | Competitive Share Jobs | Outperform Sector |
|---|---|---|---|
| **Manufacturing** | (76,072) | 7,748 | x |
| **Other Services** | 3,778 | (766) | |
| **Construction** | (11,965) | (820) | x |
| **Natural Resources and Mining** | 631 | (967) | |
| **Leisure and Hospitality** | 19,313 | (2,289) | |
| **Information** | (12,301) | (2,509) | x |
| **Public Administration** | 3,226 | (6,451) | |
| **Financial Activities** | (3,012) | (6,455) | |
| **Education and Health Services** | 83,482 | (7,291) | |
| **Trade, Transportation, and Utilities** | (14,883) | (15,214) | |
| **Professional and Business Services** | 8,466 | (26,483) | |

**Table 4**
**Connecticut Population**
**By Age Group**

| | **2000** | **2010** | **Change** | **% Change** |
|---|---|---|---|---|
| **Total Population** | 3,405,565 | 3,574,097 | 168,532 | 4.9% |
| **Age Group** | | | | |
| Pre-Adults (Under 20) | 925,702 | 915,773 | (9,929) | -1.1% |
| Young Workers (20-34) | 639,211 | 648,275 | 9,064 | 1.4% |
| Mid-Career Workers (35-54) | 1,061,856 | 1,060,035 | (1,821) | -0.2% |
| Older Workers (55-64) | 308,613 | 443,452 | 134,839 | 43.7% |
| Retirees (65 and Over) | 470,183 | 506,559 | 36,376 | 7.7% |

**Table 5**
**U.S. Population by Age Group**

| | 2000 | 2010 | Change |
|---|---|---|---|
| **Total Population** | 281,421,906 | 308,745,538 | 27,323,632 |
| **Age Group** | | | |
| Pre-Adults (Under 20) | 80,473,265 | 83,267,556 | 2,794,291 |
| Young Workers (20-34) | 58,855,725 | 62,649,947 | 3,794,222 |
| Mid-Career Workers (35-54) | 82,826,479 | 86,077,322 | 3,250,843 |
| Older Workers (55-64) | 24,274,684 | 36,462,729 | 12,188,045 |
| Retirees (65 and Over) | 34,991,753 | 40,267,984 | 5,276,231 |

**Table 6**

| Age Group | Average Population | CT Effect | Percent |
|---|---|---|---|
| Pre-Adults (Under 20) | 920,738 | (42,072) | -5% |
| Young Workers (20-34) | 643,743 | (32,144) | -5% |
| Mid-Career Workers (35-54) | 1,060,946 | (43,498) | -4% |
| Older Workers (55-64) | 434,811 | (196,692) | -45% |
| Retirees (65 and Over) | 429,593 | 100,761 | 23% |

**Figure 1**

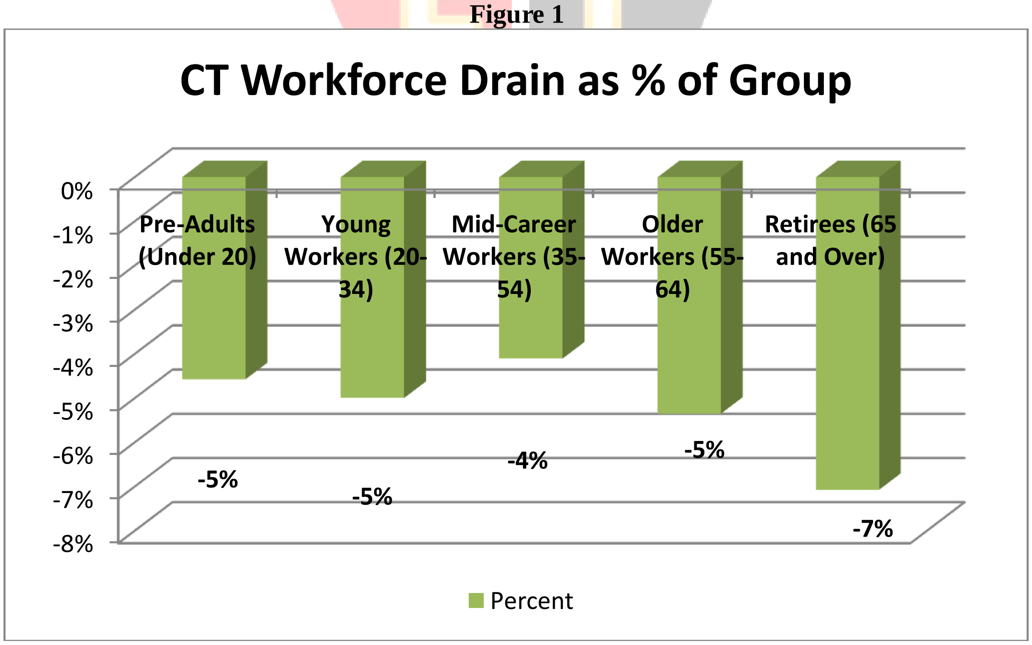

**Figure 2**
**Goolge Search Volume for the State of Connecticut**
**Terms: mba & gmat**
**January 2004-August 2013**

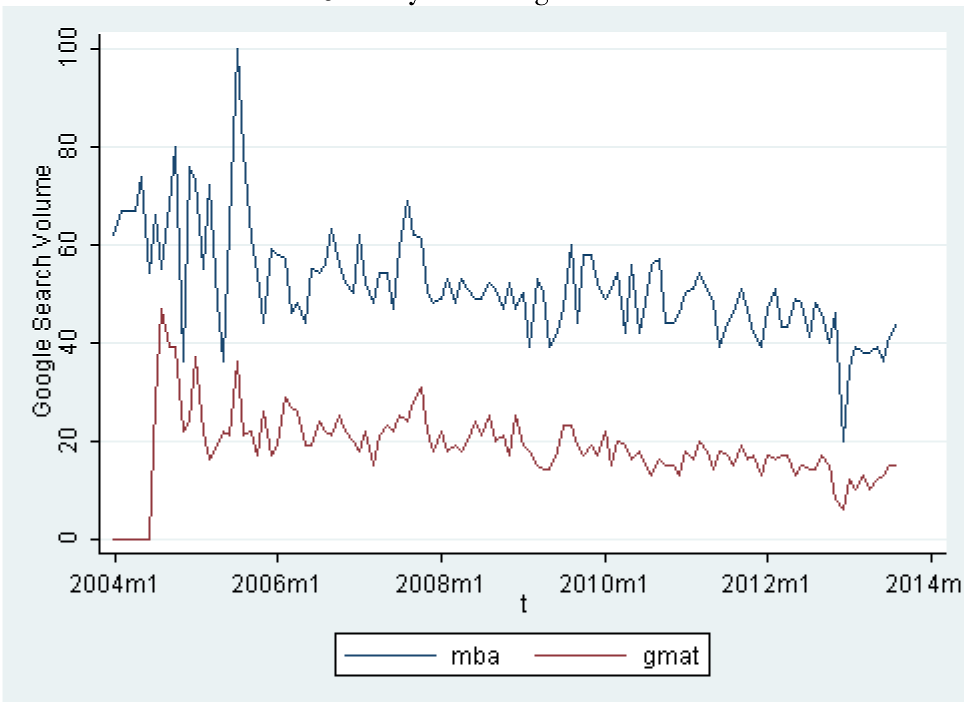


**Table 7**
**Results of Search Volume Model**

| | Ln(gmat) | Ln(mba) |
|---|---|---|
| Time | -0.006 | -0.003 |
| | *(9.56)*** | *(7.07)*** |
| Constant | 6.690 | 5.861 |
| | *(17.17)*** | *(21.68)*** |
| Observations | 101 | 107 |
| R-squared | 0.48 | 0.32 |

*Absolute value of t statistics in parentheses*
** significant at 5%; ** significant at 1%*