Exploring alternative Futures Using a Spatially Explicit Econometric Model[1]

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Abstract

This paper illustrates the application of various forecasting methodologies in constructing multiple scenarios for the state of Maryland using Long term Inter Industry Forecasting Tool that tracks inter-industry outputs at a macro scale, and State Employment Model that disaggregates these outputs to the states. We then use accessibility, land availability and observed relationships of employment categories to distribute employment at a county level. In this paper, we identify the possible advantages and pitfalls of using large scale economic models to drive employment forecasts at the county level. This framework allows for simulating the implications of macroeconomic scenarios such as changes in exchange rates and unemployment levels, as well as local land use and transportation policies on local employment and demographics. In particular, we focus on two scenarios as test cases both of which involve very different ideas about how future might unfold and their effects on land use and transportation policy prescriptions. One of the scenarios involves, among others, rises in health care spending over the next few years and the other involves increases in energy prices. As will be shown, they have different spatial effects and suggest different policy actions on the part of various governments.

[1] This paper uses substantial work of Tommy Hammer (hammer@triad.rr.com). The authors also wish to acknowledge the excellent work of graduate research assistants Shuo Huang and Gregory Vernon.

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Introduction & Background

This paper demonstrates a loose coupling between a CGE model at the national level and demographic and employment allocation model to project multiple futures for the state of Maryland. The extent of the study area is shown in Figure 3 which is in part determined by the transportation model to which these models are further coupledand the requirement that the Metropolitan areas be kept in one piece. In this paper, we describe briefly the nature of the models, the coupling and the comparison of two scenarios; 1) a scenario in which current trends in the US about high health care costs continue and increasing productivity (BASE) and 2) a scenario in which high fuel prices and agricultural prices with increased spending occurs (CGS). The purpose of the paper is to demonstrate the differential effects of these futures in which neither is certain but both are likely. It is useful to plan for these multiple futures so that policies that are adopted are robust.

The Maryland Scenario Project is an exercise led by the National Center for Smart Growth (NCSG) designed to explore alternative futures for the state of Maryland and to identify what policies should be adopted today to maximize the likelihood of more desirable future outcomes. The project began with a public participation exercise called Reality Check Plus that engaged over 850 Maryland residents in four corners of the state. In these exercises participants were asked to identify principles that should guide long-term decision making and to indicate by placing legos on maps where future growth should take place. Shortly after these exercises, a Scenario Advisory Group (SAG) was formed to consider in more depth the critical driving forces and public policies that will shape the future economic, social, and environmental characteristics of the state. With the information obtained from the SAG, the NCSG is now developing formal scenarios that can be evaluated using quantitative evaluation methods.

For the Maryland Scenario Project to help shape public policy and inform the State Development Plan, which is currently under works, the scenarios constructed and subsequently evaluated must be plausible, internally consistent, sensitive to key uncertain parameters or events, and capture the effects of policy decisions. For this reason, the NCSG is now developing economic, transportation, land use, and environmental models. This modeling infrastructure will be used not only to develop distinct alternative futures, but also for computing quantitative indicators of those futures and identifying policy decisions that increase the likelihood of more desirable outcomes and preparing for those futures that are still possible. This paper presents an analysis of one element of that modeling infrastructure now under development: economic models and economic forecasts.

The results presented in the paper are produced by the framework described in Figure 1 and are further elaborated in the subsequent sections. While parts of this model have long history and are very well developed, the other parts should be considered provisional.

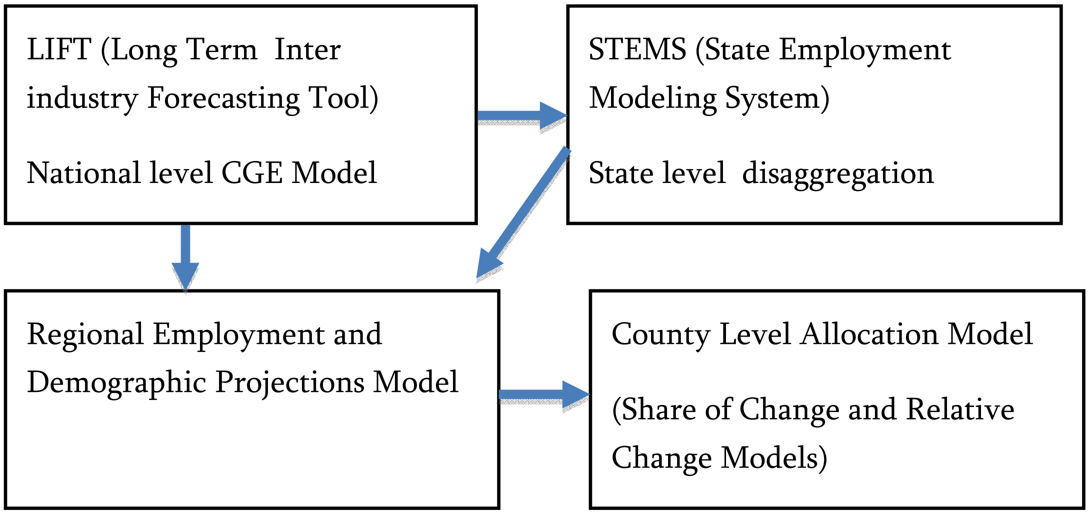

Figure 1 Scenario Projection Framework

Earlier Work

Much work in regional science and planning has focused on projecting county level employment and demographics. Perhaps, this is the artifact of the ease of availability of the spatial resolution of the data within the U.S. For example, Clark (1996) looks at the growth trends at the county level in the United States from 1981-1989. Clark builds on Carlino and Mills (1987) model of employment to conclude that for a region to have a significant change in employment and population, policymakers must implement many policies such as an improvement to the fiscal conditions, business conditions, community characteristics and amenities.

Isserman (1984) critiques the use of projections instead of forecasts because it is presumed that while projections are merely conditionals on the input variables without any judgment exercised about the nature of the inputs. However, such critique is usually leveled against projections based on past trends instead of considerations of key uncertainty about the parameters that generate these forecasts. In particular, scenario planning or planning for plausible futures and not just likely futures, is beginning to gain traction (e.g. Isserman, 2007; van der Heijden, 1996; Dewar, 2001)

West (1996) also argues a methodology of regional economic forecasting should not be restricted to a single technique; rather the methodology should include multiple analyses to better the research. In this sprit, we loosely couple various models to determine the impact of key uncertain parameters on the future of regions around Maryland.

In this paper, similar to Boarnet (2005) we need to explicitly account for the spatial structure of the region because of the geographical proximity and economic interconnectedness. Especially Washington, DC region being the seat of the federal government has a spill over effects on the rest of the states such as Maryland and Virginia. These effects are treated using in a gravity model frame work of accessibility of jobs and households.

Furthermore, by linking

LIFT Model

The Inforum LIFT (Long-term Interindustry Forecasting Tool) model is unique among large-scale models of the U.S. economy in that it is based on an input-output core, and builds up macroeconomic forecasts from the bottom up (see e.g. Meade, 2001; McCarthy 1991) Investments are made in individual firms in response to market conditions in the industries in which those firms produce and compete. Aggregate investment is simply the sum of these industry investment purchases.

Decisions to hire and fire workers are made jointly with investment decisions with a view to the outlook for product demand in each industry. The net result of these hiring and firing decisions across all industries determines total employment, and hence the unemployment rate. In the real world economy pricing decisions are made at the detailed product level. Though we cannot work at this level, modeling price formation at the 2- or 3-digit commodity level certainly captures the price structure of the economy better than an aggregate price equation. In LIFT, prices and incomes are forced into consistency through the fundamental input-output identity, and the aggregate price level is determined as current price GDP divided by constant price GDP.

Despite its industry basis, LIFT is a full macroeconomic model, with more than 800 macroeconomic variables determined either by econometric equation, exogenously or by identity. The econometric equations tend to be those where behavior is more naturally modeled in the aggregate, such as the personal savings rate, or the 3-month Treasury bill rate. Hundreds of identities are used to collect detailed results into aggregates, and then to form other aggregate variables by equation or identity. For example, total corporate profits are simply the total of corporate profits by industry. An equation for the effective corporate tax rate is used to determine total profits taxes, which is a source of revenue in the Federal government account. Equations for contribution rates for social insurance programs and equations for transfer payments out of these programs can be used to study the future solvency of the trust funds.

Certain macrovariables provide important levers for studying effects of government policy. Examples are the monetary base and the personal tax rate. Other macrovariables, such as potential GNP and the associated GNP gap provide a framework for perceiving tightness or slack in the economy.

The model loop begins on the real side, where the expenditure components of GDP are calculated in 1987 constant dollars. Before starting the expenditure calculations, estimates of final demand prices are made, based on the best current estimate of producer prices by product. Next, the savings function is called, to determine how much of real disposable income will result in total expenditures on consumption. From total expenditures, total population and an income distribution function, we calculate the distribution of per-capita expenditures for five income classes. The cross-section equations of consumption per age-weighted population are calculated next. Once this is done, relative consumption prices, age-weighted population and consumption per age-weighted population are combined in the PADS (Perhaps Adequate Demand System) function to get consumption by category. PADS allows the classification of consumption goods into related expenditure groups.

For example, the first 14 consumption categories are in the food group. The first 3 of these are in the meat and poultry subgroup. PADS also allows for group, sub-group and individual commodity price parameters. Motor vehicles prices affect the demand for public transportation, since motor vehicles and public transport are substitutes. After personal consumption, exports are calculated. If the model is run with the Inforum bilateral trade model (BTM), then exports are exogenous. However, if one wants to relax the dependence on BTM, then export equations are available which use information from BTM in the form of weighted foreign demands and foreign prices. The equipment investment equations are based on a Diewert cost function that models the substitution (or complementarity) of equipment capital with labor and energy. The equations use a cost of capital measure that includes real interest rates, present value of depreciation, investment tax credit and corporate profits tax. The construction equations are for the roughly 20 categories of private construction. Though each has a different form, common variables are interest rates, disposable income and sectoral output.

Federal, state and local consumption and investment expenditures are specified exogenously in real terms, but LIFT allows for detailed control of these expenditures. For example, defense purchases of aircraft can be specified independently of missiles, ships or tanks. Capital consumption allowances of government are endogenous, based on depreciation of government capital stock, which is also calculated in the model.

At this point, all final demand expenditure categories except for imports and inventory changehave been calculated. This means we are ready to use the Seidel input-output solution to solve jointly for output, imports and inventory change. Note that the A-matrix coefficients are specified to change over time, according to trends for each row. However, individual coefficients can be fixed, to model changes in price or technology.

Disaggregation Using STEMS

The Inforum STEMS provides projections of employment, output and earnings for 65 industries, for 50 states and the District of Columbia. STEMS also calculates regional aggregates for the 8 BEA regions. STEMS uses exogenous variables at the national level from the Inforum LIFT model of the U.S. Although the STEMS is driven by the national model, much of the forecast of state activity is endogenous to that state.

STEMS relates the employment by industry in each state partly to national employment of that industry, and partly to the level of personal income in that state. Industries that are assumed to mainly serve national markets are called "basic" industries, and industries that mainly serve localmarkets are "non-basic" industries. The degree to which an industry is basic (national in scope) is defined by a coefficient between 0 and 1.

State shares of employment in an industry which is basic are determined by a number of factors. An industry may locate in a state due to natural resource availability, infrastructure, availability of skilled labor, etc. For these reasons, the states shares are likely to change slowly, since the relative strength of these factors in each state changes slowly. However, other factors are also at play, such as relative wage rates in different areas, or agglomeration effects due to growth of clusters of industries in a particular location.

Once employment has been calculated, real output is derived using national ratios of output to employment by industry. This assumes that labor productivity for a given industry is the same in each state. Although this assumption is probably not true, there are no data available to identify different output to labor ratios for a given industry by state.

STEMS also calculates earnings by industry based on employment. The STEMS historical data includes earnings and employment for each industry by state. STEMS moves the state earnings to employment ratios forward in time by the movement of the ratio of (proprietors' income plus labor compensation) to employment in the forecast of the national model, LIFT.

The next step in the calculations is to calculate total personal income in each state. Personal income is formed as a function of the following six components:

1. Total earnings (wages and salaries and proprietors' income) – This is formed as the sum of earnings by industry.

2. Transfer payments – A regression for each state relates state transfers per capita to national transfers per capita, and this is transformed back to levels by multiplying by state population.

3. Dividends, interest and rental income – This equation is also estimated in per capita form, and is related to the national per capita earnings of dividends, interest and rent.

4. Contributions for social insurance – The ratio of contributions to total earnings is related to the national ratio. Note that this item is subtracted in arriving at personal income.

5. Residence adjustment – This item represents the net income that is earned in another state by residents of a given state. It is related to total state earnings, but can easily be made exogenous. Note that this number can be either positive or negative. The two "states" that have the biggest negative value for this item are New York, and the District of Columbia, which both have many commuters from out of state.

6. Personal income, in turn is an important influence on the employment and output in a given state, in the industries that have a basic coefficient less than 1. In other words, these are industries whose market is at least partly local.

STEMS iterates until convergence each year, and personal income is the variable on which convergence is tested. For the model to be considered solved in any given year, the difference of personal income in every state for this iteration minus the value in the previous iteration must be very small.

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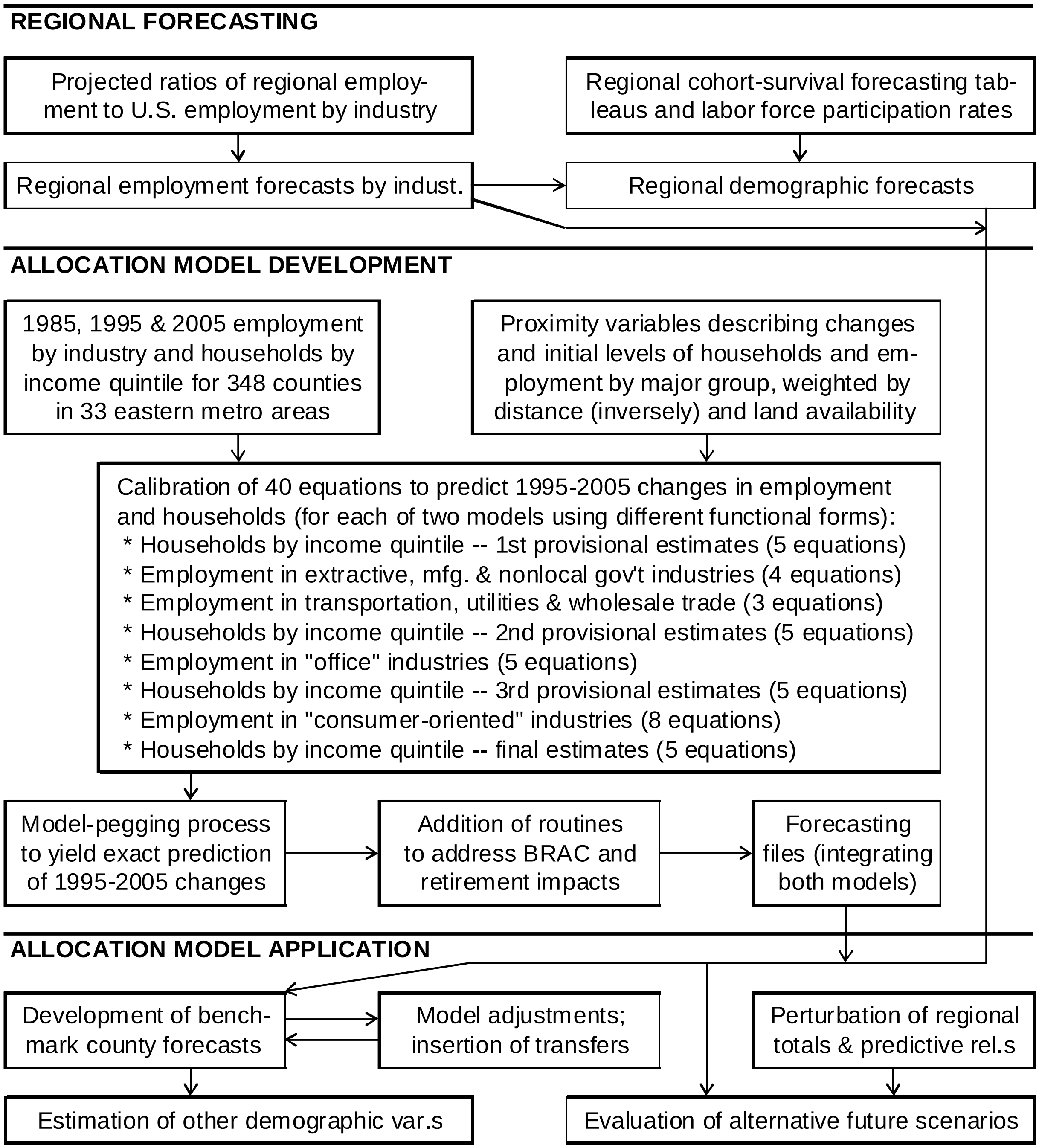


Figure 2 Regional Forecasts and County Allocation Methodology

Regional Forecasts and County Allocation Models

The National outputs are disaggregated into State level outputs by STEMS which then informs the regional forecasting as described in the Figure 2. The regions with in the study area are described in Figure 3, primarily consisting of the Washington Baltimore Region, Philadelphia region, Eastern Shore of Maryland and Delaware region (Peninsula region) and the Western Maryland region. At this level the demographics and employment is projected based on the

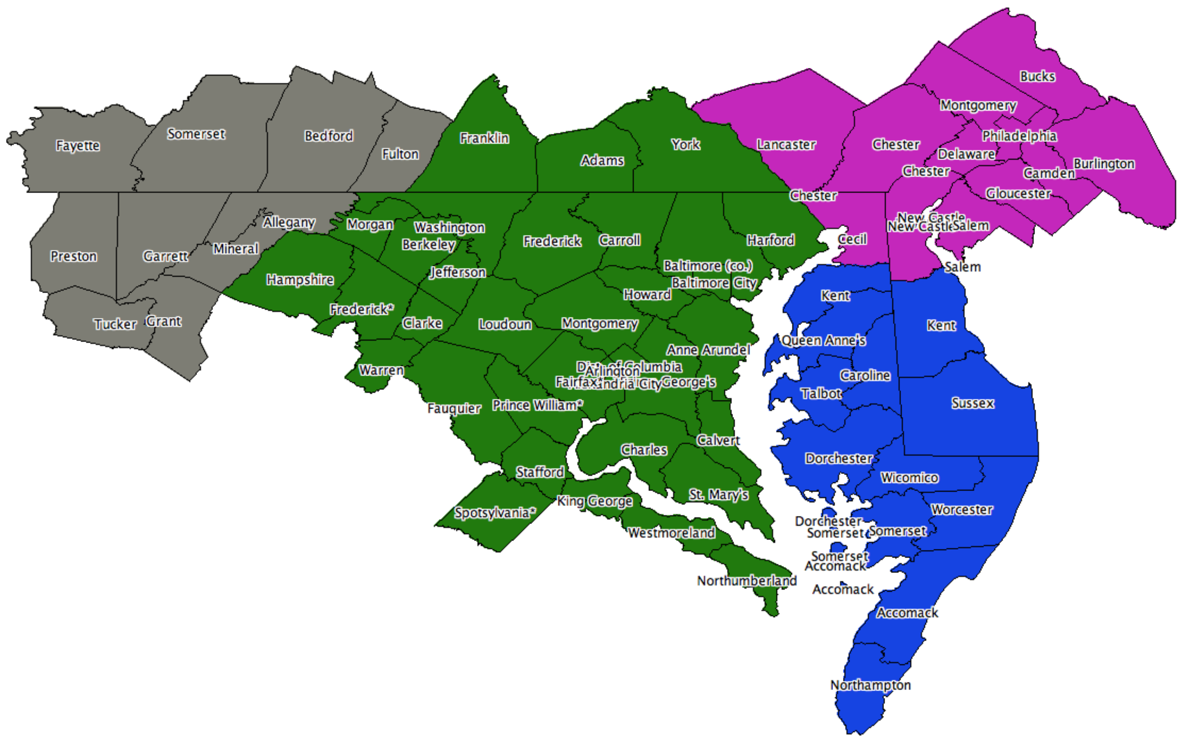


Figure 3 Regions in the Study Area

ratios of the region's employment to the nation in each sector. The predicted future ratios were then applied to the forecasted levels of national employment in the given industry to yield a regional forecast covering all years through 2040. Total regional employment simply equaled the sum of these industry forecasts. The regions differ a good deal in comparisons involving past growth and U.S. trends, as shown by Table 1below. Demographic variables (such as households) are tied to the employment using a standard cohort component analysis. This paper merely alludes to these variables without detail, for want of space.

Table 1Annual rate of growth in employment different regions in the study area

	Actual	Actual	Actual	Forecast
	1990-95	1995-2005	1990-2005	2005-40
United States	1.14%	1.25%	1.21%	0.73%
Wash.-Balt. Region	0.09%	1.64%	1.12%	0.90%
Western Region	0.83%	0.67%	0.72%	0.37%
Philadelphia Region	-0.25%	1.09%	0.64%	0.37%
Peninsula Region	1.18%	1.70%	1.52%	1.05%

The calibration and application of a system of equations for region-to-county allocation is the pivotal element of the present forecasting approach. The model calibration sample is consisted of 348 counties in 34 metropolitan areas, collectively containing roughly a third of the nation's population and employment. These metro areas –referenced hereafter as regions – included all MSAs and CMSAs of a million-plus population in the eastern U.S. except Miami, New York and the metro areas in New England. (The Miami MSA spans only two counties and the metro areas from New York northward are nestled too closely to avoid boundary problems.) The target variables consisted of employment in 20 NAICS-based industry groups and households in five relative income groups. The income groups were quintiles defined on a regional basis, meaning that each group accounted for 20% of each region's households in each year. The allocation model was structured to predict changes in the target variables across ten-year intervals. The calibration interval was 1995-2005, with past-change predictors pertaining to 1985-1995 and forecasted forward from 2005 for every 5 year increments.

The calibration process consisted of using multivariate statistical analysis to "explain" 1995-2005 changes in each category of employment and households across the 348-county sample. The predictors tested in the equations expressed past changes, initial conditions and current changes in the employment and household groups under analysis, usually embedded in complex functions as explained momentarily.

To simulate urban dynamics realistically, an allocation model must at minimum have the capacity to: 1) express interactions among all combinations of economic sectors and household groups; 2) capture the influence on each area (county) of events in nearby areas; and 3) register the growth-retarding effects of reductions in land availability for development. The approach applied here met the first criterion by treating employment and households on a fully integral basis, with all sectors tested for influence on all other sectors. The second criterion, relating mainly to spillover of growth from one urbanizing area to the next, was met by structuring most predictors as "proximity" measures that covered past, initial or current conditions in all areas of a region rather than just the area to which a measure pertained. These quantities were computed as sums of changes or initial conditions inversely weighted by distance from the subject area, using a formula containing parameters that were varied to yield multiple variables for testing. The third criterion was met by including an index of land availability as a weighting factor in all proximity variables, bearing an exponent that became sector-specific in the calibration process. The multiplicative form allowed each predictor to balance the advantages of centrality – i.e., nearness to existing development and growth – against the advantage of greater land abundance at less central locations.

In this approach, the immediate products of the calibration task are actually two models, i.e., two separate sets of predictive equations for all household and industry groups. The

Table 2 Dependent Variables in the Alternative Models

Units of observation: counties (and independent cities) grouped by region
Quantity under analysis: Y = employment in some industry or households in some quintile
Objective is to explain change in Y from year t to year t+1
Let $\bar{Y}$ denote the regional sum of Y (with subscript to denote year)

Relative-Change Model

Null hypothesis: All counties gain Y at the same percentage rate, i.e., at the regional rate.
Dependent variable is difference between the observed value of Y_{t+1} and the value that would have prevailed given growth from year t at the regional rate
Dependent Variable is of the form (before including divisor)

$$Y_{t+1} - Y_t * \left(\bar{Y}_{t+1} / \bar{Y}_t \right)$$

Dependent variable sums to zero, and all independent variables are structured to have zero sums (before application of denominator).
Liability of model: Dependent variable is likely to be dominated by a relatively few large observations (problem of heteroscedasticity).
Solution is to divide both sides of the linear regression equation by a quantity that is constant for each observation but varies across observations.

Divisor is of the form

$$\left(E_t * Y_t / N \right)^{.25}$$

where E is total employment in the county

and N is the number of counties in the region.

In this model the dependent variables are structured similarly as deviations from expected levels (based on regional changes or sectoral distributions), and include the same divisor. However, the divisor is set aside when the equation is applied for predictive purposes

Share-of-Change Model

Quantity analyzed is each county's share of regional change in Y from year t to year t+1 (times number of counties in region to yield a mean of unity for each region).

Liability: Shares of change are meaningless unless regional change is appreciably positive and nearly all county changes are positive.
Consequently change must be computed relative to a discounted initial value.

$$N * \frac{(Y_{t+1} - k * Y_t)}{\sum_R (Y_{t+1} - k * Y_t)}$$

where k is a parameter determined when fitting the equation

where summation in the denominator is for all counties in region R

All dependent variables are shares of regional change, or ratios to regional means, summing to unity for each region after weighting by N (number of counties)
Complication: R-square is inflated because part of what's being explained (namely the portion of Y_{t+1} equaling (1-k)*Y_t) consists of activity that's already present.
Also R-square is inflated because null hypothesis states that growth in Y (absolute, not %) is the same in all counties, which is grossly implausible.
Resolution is to use ordinary significance tests when developing each equation for a given value of k, but to select among equations on the basis of unexplained variance in Y_{t+1} rather than the dependent variable as analyzed
In this model the independent variables are all structured as shares of change.

Table 3 Computation of Proximity Measures

Most predictors tested in the model equations incorporate so-called proximity measures. These are obtained by summing activity levels across all areas (counties) of a region when weighted inversely by distance to the area for which the measure is being computed.

Each proximity measure pertains to one of the nine major types of activity covered by the model (i.e.,to employment in one of four major industry groups or households in one of five Income groups). Here the targeted activity can be referenced simply as "A" without subscripts indicating the type of activity or year of coverage. A proximity measure "P" for area "j" is then computed as follows (where the summation across i includes area j):

$$P_i := \sum_{j \in R} \frac{A_i}{\left(D_{ij} + g_j + f\right)^r}$$

where: A_i is the level of the given activity in area i;
D_{ij} is the distance between areas i and j;
f is a "terminal time" parameter (in miles); and
g_j is an estimate of internal travel distance in j.

The internal distance term g_j is a function of j's land area in square miles. This function includes a parameter h. Thus computing a proximity measure requires assumed values of three parameters: f, h and the exponent r. A standard procedure is to compute three versions of each proximity measure using the following three sets of parameter values:

r = 2	r = 2.5	r = 2.5
f = 5	f = 5	f = 3
h = 5	h = 5	h = 3

When both types of models were calibrated for this project, the variables that were found most significant overwhelmingly involved the last of these three sets of parameter values (as often holds). Hence the final equations have been limited to measures incorporating these values.

Computation of Land Availability Term

In the dynamics of urban development, proximity to an attractant (activity) is interactive with the amount of land available for development. Impact on growth goes to zero as either proximity or land availability goes to zero. Hence the independent variables that Incorporate proximity measures always multiply these measures by a land availability term. The land availability term always pertains to the initial year of the prediction interval – i.e., to year t -- even though it may multiply proximity measures pertaining to two different years. It is defined as follows (omitting the subscript t):

$$V := \left(\frac{(L * c) / (c + W)}{\overline{(L * c) / (c + W)}} \right)^{s}$$

where: L is land area in square miles;
c is a constant;
s is an exponent to be determined

W is a linear combination of employment levels by industry and households by income

The denominator is the average over the counties in the region

The best-fitting value of the exponent s is determined by trial-and-error in the course of fitting an equation. (The fact that the exponent can go to zero allows for the possibility of no land-availability influence, a finding sometimes obtained for industrial and office functions.) The present project has used previously estimated values of c and the parameters in W.

functional forms used in allocation models are constrained by the need to achieve exact allocations of fixed regional totals (i.e., total increments). No form meeting this constraint is fully satisfactory, so the chosen strategy is to use two different functional forms. In a "relative-change" equation, the quantity being predicted equals the difference between an area's actual (or forecasted) change in some sector and the change that would be observed if all areas in its region gained this activity at the same percentage rate. The explanatory variables are similar constructs, or consist of differences from "expected" shares in the initial year, so that each variable on each side of the equation sums to zero for each region. This functional form involves a relatively plausible null hypothesis (which supports the meaningfulness of significance tests and R-square), but creates serious exposure to heteroscedasticity problems.

The alternative is a "share-of-change" equation in which the dependent variable is simply an area's share of regional change in some sector. The independent variables are expressed as shares of change or initial activity, so that all variables sum to unity for each region. A problem with this formulation is that variables dealing with increments must be computed using discounted values of initial-year activity to keep their regional sums appreciably positive. The discounting requirement introduces an additional parameter that complicates the calibration process. Yet share-of-change equations typically exceed relative-change equations in predictive power at least half the time.

The model calibration task in the present study calibrated full sets of "relative-change" and "share-of-change" equations and developed forecasting spreadsheets that applied to both. For each sector the predictions were then combined with weightings that reflected the relative accuracy of the two equations in replicating study-area changes during the calibration interval.

A special aspect of the present effort was the geographic coverage of proximity variables. In most studies of this type, the summations of distance-weighted quantities in proximity variables only extend across the home region of the area being addressed. Such an arrangement would be suboptimal in the present case, however, due to interactions across regional boundaries, such as the spillover of growth from Washington-Baltimore to Maryland's Eastern Shore. Hence the proximity-variable computations were expanded in two ways. First, the summations for counties in the Peninsula and Philadelphia regions extended across parts of Washington-Baltimore (covering most counties east of the District and north of Baltimore, respectively). The Peninsula summations also covered New Castle and Cecil counties in the Philadelphia region. Second, the proximity-variable computations for three regions also covered external metropolitan areas, each treated as a single point. The Western region computations covered the Pittsburgh MSA; those for Washington-Baltimore covered the Harrisburg MSA; and those for the Peninsula region covered metro Virginia Beach-Norfolk. As part of the regional forecasting task, independent forecasts were obtained for these three external MSAs in the same fashion as described for other regions.

The tables on the next two pages describe the leading model features in more formal terms. The first deals with the two different model types, focusing mainly on the functional forms in which dependent variables were analyzed and quantities predicted. The second table describes the computation of proximity measures and land availability terms. Most independent variables were products of these quantities, embedded in functional forms consistent with their dependent variables. (For example, they were expressed as regional shares in the share-of-change model.)

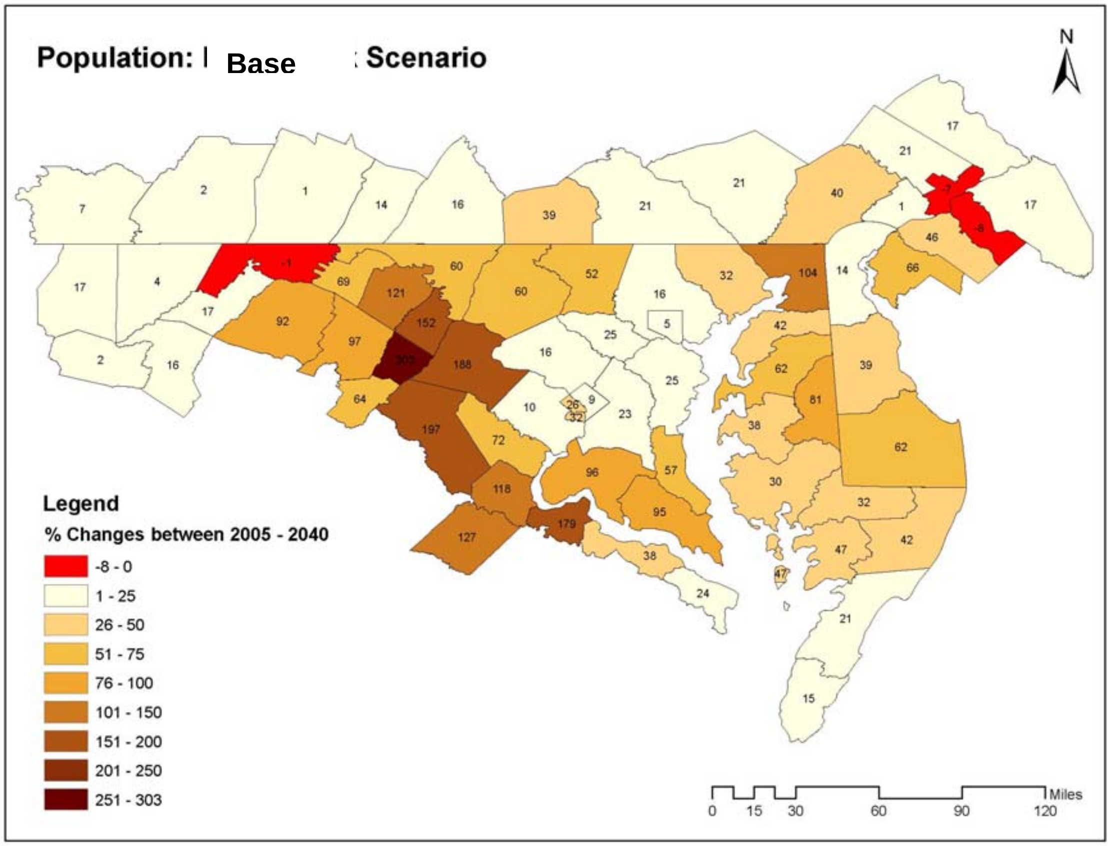


Figure 4 Percentage change in the population from 2005 - 2040

Figure 4 describes the outcome of the weighted average of the allocation models for population. As it can be seen in percentage terms, the central part, the Washington Baltimore region experiencing only modest increases of less than 25% where as the second ring counties experience much larger percentage growth. Some of it can be explained due to higher 2005 numbers in the central corridor, but the allocation also predicting the

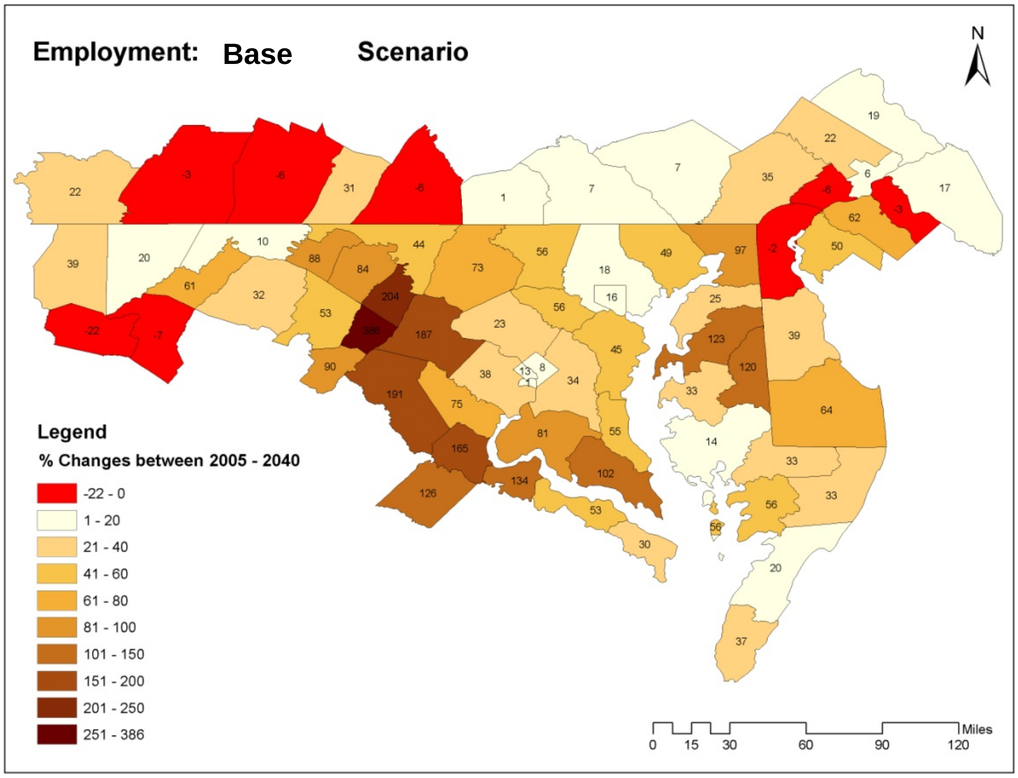


Figure 5 Percentage change in the Employment from 2005 - 2040

continuation of the trend, puts more population in these counties. Only three counties experience declines and are shown in red.

Figure 5 on the other hand, shows much larger geographic variation of the total employment. The central corridor(with the exception of the city of Baltimore and D.C.) has substantial increases in employment in percentage terms. However, D.C while still growing by 8% is substantially higher than Queen Anne's county on the Eastern Shore which is projected to grow 1.2 times. (80,000 vs. 25,500). Nevertheless, the pattern of growth represented here, shows that larger share of the future growth moves to the non urbanized counties, both as a result of the trend as well as the availability of the land.

Furthermore, this result should be taken only as a benchmark against which other scenarios are compared to. It is to this we turn to in the next section.

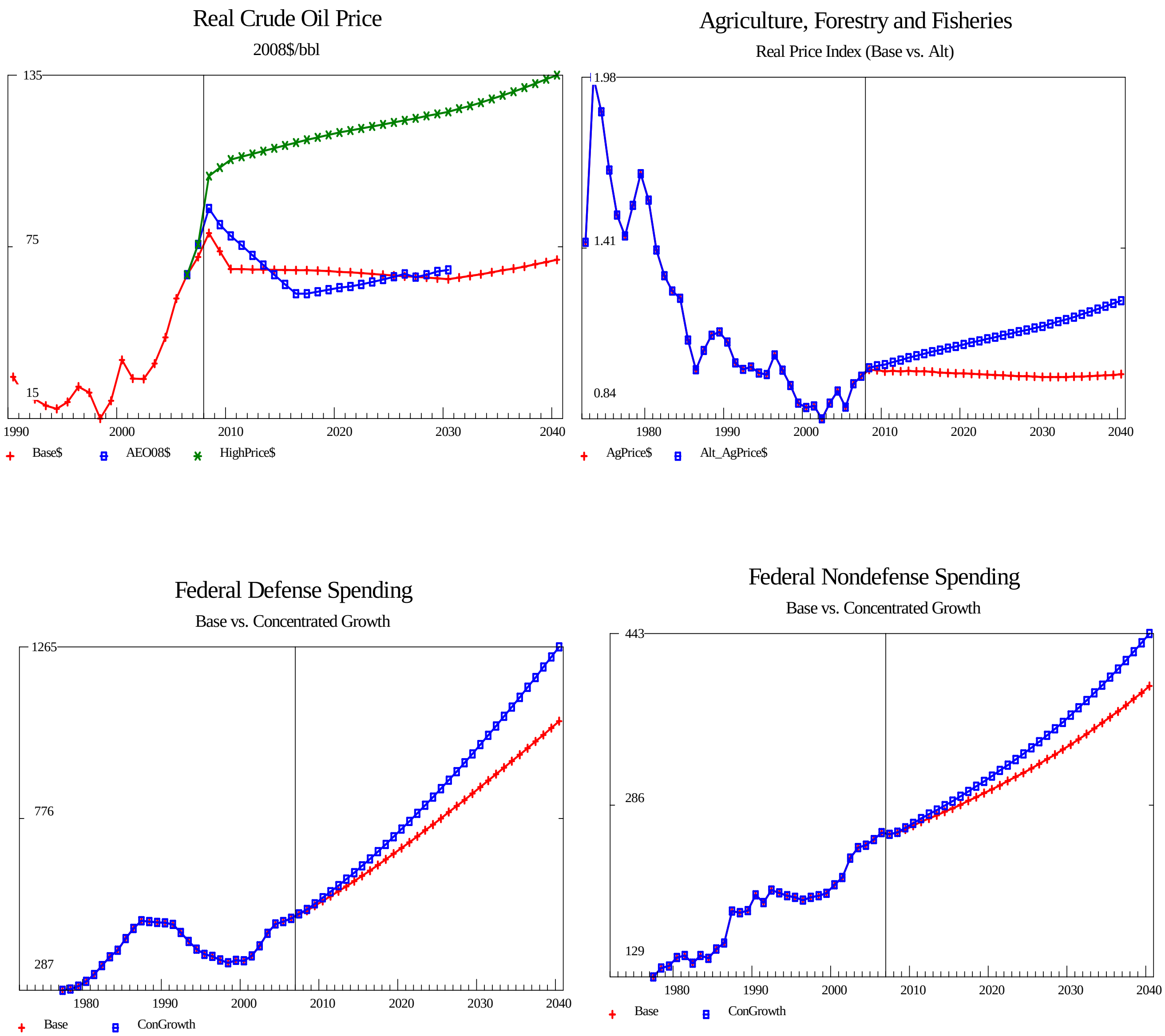


Figure 6 Assumption of selected scenario inputs into LIFT

Scenario Assumptions

The differences in the exogenous inputs to the LIFT Model between the scenarios are laid out inFigure 6. Further explanations are below. The purpose of the scenario is to hypothesize about a plausible future not necessarily a likely one.

Oil Price Assumption - Figure 4 shows a hypothetical path for the nominal ($/bbl) crude oil price for our alternate case. I've compared it to our existing Smart Growth Base (same as the Inforum Base Outlook assumption for Crude oil price, from November 2007), and the DOE/EIA *Annual Energy Outlook 2008,* released in June 2007. Note that for the high path, I projected the nominal price to grow at 3% after 2010, which is about inflation plus 1 percent.

Agriculture Price Assumption - The assumption for the alternate case is a price index for Agriculture, Forestry and Fisheries that is 25% higher than the base by 2040 in real terms, that is, adjusted for general inflation. Observe that the real agriculture, forestry and fisheries price index has been generally falling over time, since about 1975. Our base case assumption was for an Ag price that rose slightly slower than general inflation, remaining almost constant in real terms. This is consistent with the USDA Baseline (although their projection only goes to 2017.)

Biotech / Infotech / R&D - These activities are concentrated heavily in two industries: 48: Miscellaneous professional, scientific and technical services 49: Computer systems design and related services. Both of these industries sell a large portion of their output to other industries (intermediate). To model the increased activity, the input-output coefficients of each industry to the major consuming industries were increased relative to the base case. The coefficients were assumed to become 20 percent higher than the base by 2040, indicating more intensive use of these industries by other industries.

Finance and Insurance (41-44) - Slightly more than half the output of these industries is sold to personal consumption. The major part of the remainder is sold to intermediate demand. Intermediate demand was increased in the same way as for industries 48 and 49. Finance and insurance consumption categories were also made to rise faster than the base.

Changes in the county allocation methods -Since the allocation of demographics and employment in the base case are calibrated against history, any changes in structure of the relationships that are imposed by the high fuel prices and others are not adequately captured. A seminal exposition of this problem is identified in the Lucas critique (Lucas 1976). If the same equations are allowed to allocate in both base and concentrated growth scenario, there is a mismatch of assumptions at two levels of model. As such in the high fuel price scenario, it is assumed that jobs and households choose to locate closer to each other. This is achieved by diverting a percentage of household growth (2/3 in the case described for this paper) for allocation on another basis. The other basis consists of a single variable expressing a county's access to employment throughout the region, multiplied by the county's value of the land availability index. For the lack of better term, this is called employment access variable given by equation

$$EA_i = \sum_{c \in R} \frac{(E^c * L^c)}{(D_{ic} + g + f)^r}$$

where i and c are counties in region R, D is the distance between them, L is the land availability index as defined by the above equation.

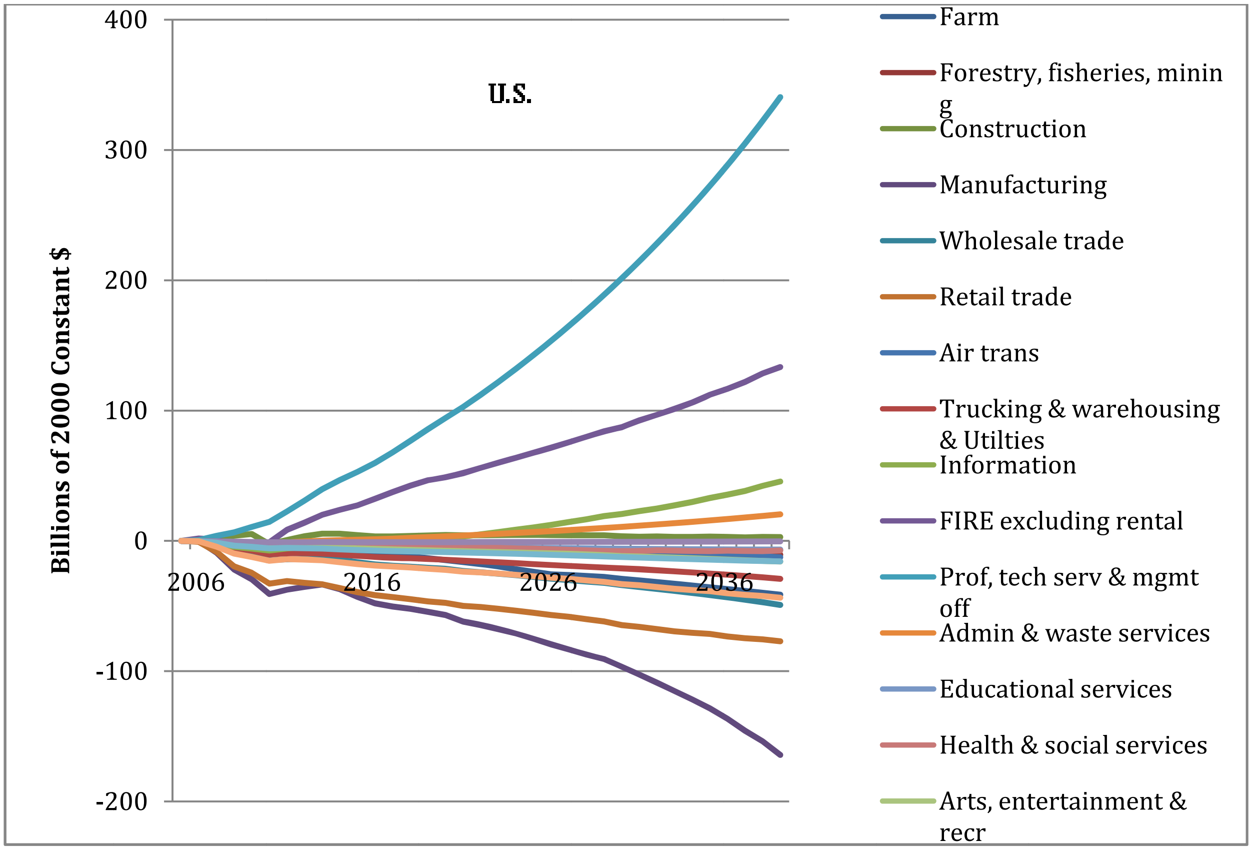
It's computed using total (i.e., all-industry) employment in the initial year of a given forecast interval, using the same type of gravity computation that the model deploys in obtaining access measures. This is tantamount to assuming that the tendency of high fuel cost to concentrate future development will be driven by the attempts of households to reduce commuting distances, rather than by independent attempts of employers to stay close together. Given the tight integration of households and employment achieved by the new allocation model, this assumption is believed to yield adequate modification of employment patterns, which remain more concentrated than household patterns in any case.

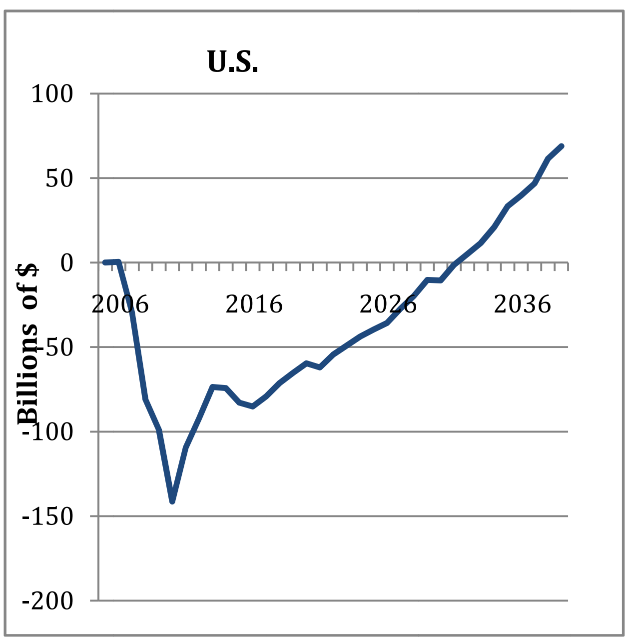
Comparing Outputs

The differences in the national outputs as produced by LIFT is shown in the Figure 7. Predictably the Maryland economy does better than the nation as a whole because of heavy concentration of the Professional services and other industries that are not entirely dependent on fuel prices. However, the shock of the fuel and agricultural prices are felt in both economies though due to the equilibrium nature of the LIFT model the economy performs corrects itself and reverses the decline by 2011, but actually has an increase in output by 2030 for the US and 2015 for Maryland. This difference is primarily due to heavy concentration of increases of federal defense and non defense funding and its implications on DC, MD and northern VA region. Increases in agricultural prices may result in lower rates of urbanization, however, decreases output in the farm sector due to competition from international food prices that are kept fixed in the model. Being a General Equilibrium model, LIFT and STEMS reverts to equilibrium path even in the presence of shocks at times over correcting. This explains the reason why the economy performs better than the base in the CGS even with higher than usual fuel prices. Furthermore, increases in federal spending also buoys the economy though affects Maryland and DC disproportionately to the rest. This is apparent from the annual growth rates (see Table 4) in the number of jobs in both scenarios. The decline in the FIRE sector is attenuated in the CGS than in BASE due to the increase in the personal consumption equations of this particular sector.

Table 4 Annual employment growth rates between 2006-2040 in various industries

Industry	U.S.		Maryland	
	Base	CGS	Base	CGS
Farm	-0.90%	-1.14%	-0.86%	-1.06%
Forestry, fisheries, mining	-0.76%	-0.89%	-0.97%	-1.10%
Construction	1.07%	1.10%	1.12%	1.20%
Manufacturing	-0.07%	-0.13%	0.14%	0.10%
Wholesale trade	0.00%	-0.06%	0.13%	0.12%
Retail trade	-0.56%	-0.69%	-0.44%	-0.51%
Air trans	2.18%	2.11%	2.25%	2.22%
Trucking & Utilties	0.43%	0.36%	0.59%	0.56%
Information	0.24%	0.26%	0.21%	0.27%
FIRE excluding rental	-0.46%	-0.15%	-0.39%	-0.09%
Prof, tech serv & mgmt off	0.09%	0.38%	0.25%	0.56%
Admin & waste services	0.40%	0.46%	0.45%	0.55%
Educational services	0.68%	0.60%	0.86%	0.82%
Health & social services	2.14%	2.11%	2.34%	2.36%
Arts, entertainment & recr	0.93%	0.75%	1.00%	0.86%
Accommodations	-0.31%	-0.32%	-0.29%	-0.27%
Food services	0.22%	0.15%	0.34%	0.31%
Other services incl rental	0.26%	0.19%	0.38%	0.35%
Federal gov incl military	0.26%	0.74%	0.61%	0.71%
State & local government	0.46%	0.46%	0.61%	0.64%
TOTAL	0.47%	0.48%	0.63%	0.71%





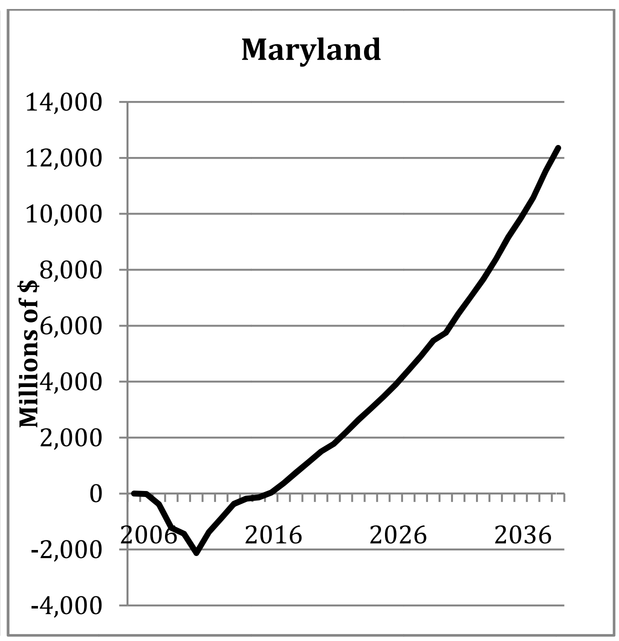


Figure 7 Difference in the Outputs between Concentrated Growth Scenario and the Base for US and for Maryland

Implications for the Study Area

We differentiate the effects of using this allocation method versus the base case allocation method in the subsequent sections. They are named alternatives A, B, C where A uses the employment distribution generated in the CGS outputs of LIFT/STEMS as well as the user of employment access variable to distribute the portion to the households, B uses only the employment access variable with the Base employment and C uses only the CGS outputs without the reallocation of the households. It should be noted that while A is the composite effect, substantial variation is due to the household allocation due to employment access variable as shown in figures 10 and 11.

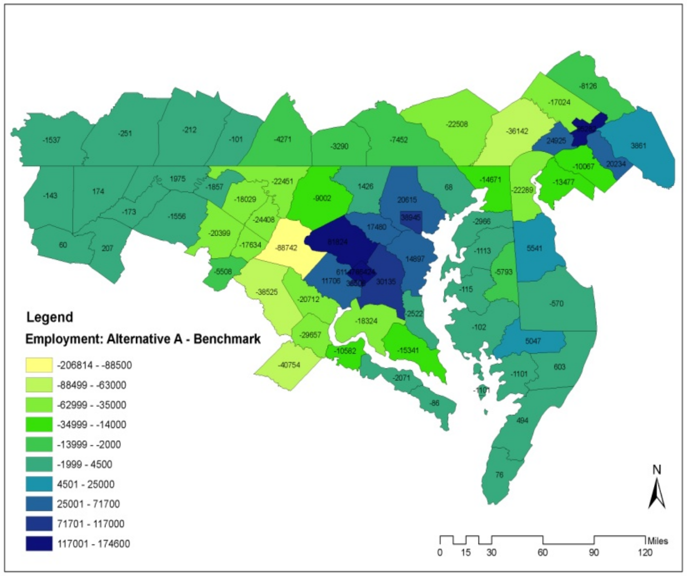
There are three explanations for the relatively modest differences in county-level forecasts produced by altering the industry mix of employment at the state and regional level. The discussion of them will focus upon the Washington-Baltimore region and the alternative that do not involve household reallocations, i.e., upon the benchmark forecast and scenario C. Only employment differences need to be mentioned since the accompanying demographic differences are derivative and even smaller. It should be noted that larger industry-mix impacts may be obtained in later scenario analyses that do not involve the restrictions noted below in the second and third explanations.

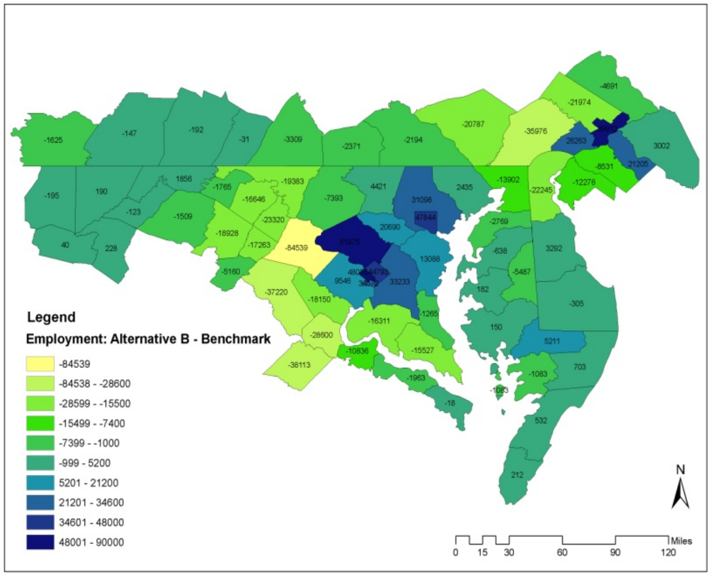
The first explanation is a matter of arithmetic. It is that the posited industry-mix differences are much smaller numerically than the demographic impacts produced by reallocating two-thirds of all households (in the alternatives A and B). The two state-level employment forecasts involve very large percentage differences for some of the individual industries in the 65-sector classification used at that level. However, many of the differences are muted when the numbers are aggregated to the 21 industries used in county forecasting. (Some further smoothing results from the norming step discussed below.) Across these 21 industries in Washington-Baltimore, the only double-digit percentage difference in 2040 regional employment is a 14% gap for federal government. No other difference exceeds 7%. Differences of this magnitude are not nearly sufficient to produce impacts commensurate with those of massive changes in household behavior, given that the latter bear more directly upon regional geography. Impacts rivaling those of the household reallocation would require a more-than-profound restructuring of the national and regional economies, which would be difficult to forecast.

The second explanation is that the allocation model predicts a good deal of geographic dispersion in all sectors, so increasing the future employment shares in industries that are initially concentrated has a smaller centralizing influence than might be expected. In illustrating this situation it is convenient to reference the "central area" of the Washington-Baltimore region consisting of the ten jurisdictions that lie between and include Fairfax County, Virginia, and Baltimore County, Maryland. A major focus of the initial analysis has been the extent to which scenarios other than the benchmark could concentrate growth in the central area and reduce sprawl into the remainder of the region. The central area contained 75% of the region's total employment in 2005, but according to the Base forecast it will capture only 49% of the region's 2005-40 employment increase.

The CGS employment forecast involves higher regional employment than the BASE forecast – the version incorporated in the benchmark computations – for four of the 21 sectors. The central area had 85% of employment in these four sectors as of 2005, but according to the benchmark forecast will capture only 69% of their 2005-40 growth. In alternative C, incorporating the SCA employment figures but without household reallocation, the central area captures 72% of employment growth in the four sectors. But when compared with their 85% initial share, the latter percentage still reflects a good deal of employment dispersion. Given that the allocation model has been calibrated to data describing past conditions that may not hold in the future, we could reduce dispersion by overriding the model equations in a fashion resembling the reallocation of households. However, for the initial analysis we have chosen to work through the model as it stands and restrict attention to industry-mix effects.

The third explanation involves total employment. The unadjusted CGS forecasts involved significantly higher total employment than the BASE forecasts for Maryland, Virginia and especially the District of Columbia. When these numbers were allocated to the Washington-Baltimore region, the difference worked out to 5% of total 2040 employment and 30% of 2005-40 employment growth. One problem presented by this situation was that using different regional employment totals for CGS versus BASE scenarios would require the development and use of different demographic forecasts (given that regional demographics were largely pegged to employment). Another was that having differences in regional aggregates would complicate comparisons among scenarios. The larger employment total in CGS forecasts would offset the larger shares of employment in centralized industries and might even yield greater sprawl in absolute terms than the BASE forecasts. Again, the resolution in the initial analysis was to restrict attention just to industry-mix effects. This was done by norming the CGS employment figures so that they had the same regional totals as the BASE forecasts. Later scenario analyses may loosen this restriction and obtain substantially different results.





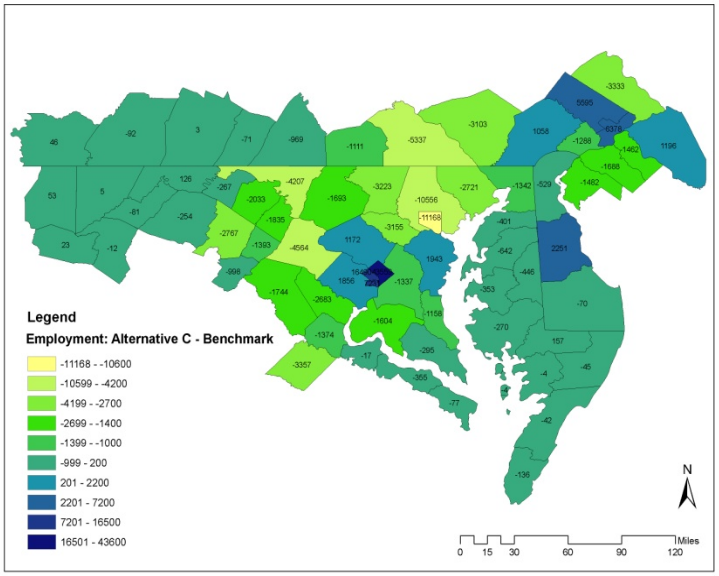


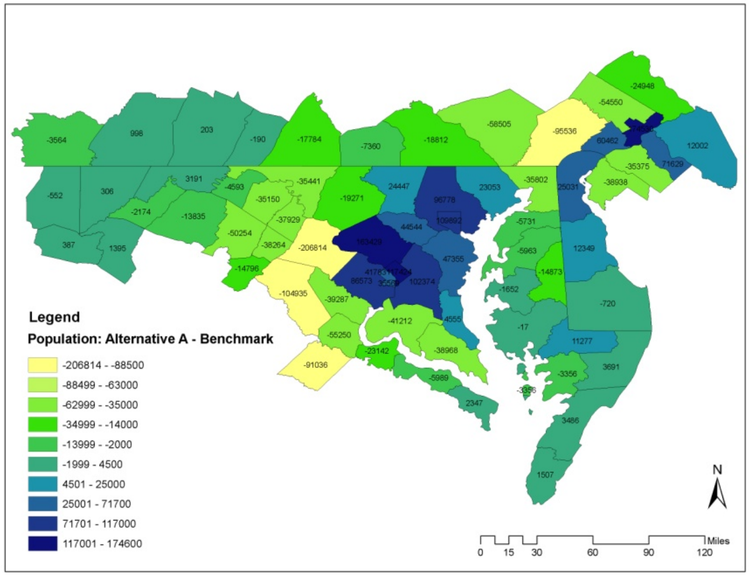
Figure 9. Differences in Employment between Base and Alternatives A, B & C

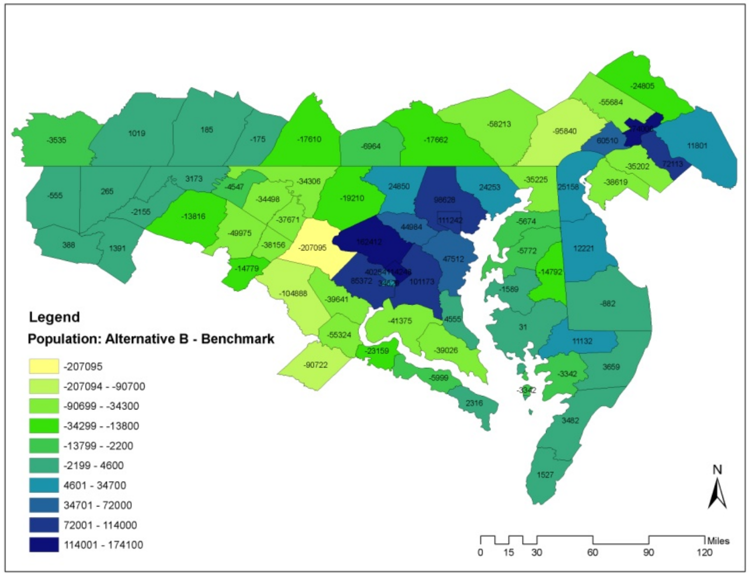
From Top left

(a) Differnce between employment allocation with both "employment access" variable on households and CGS output of STEMS (Alternative A) from the Base

(b) Differnce between employment allocation with "employment access" variable on households (Alternative B) from the Base

(c) Differnce between employment allocation with CGS output of STEMS" (Alternative C) from the Base





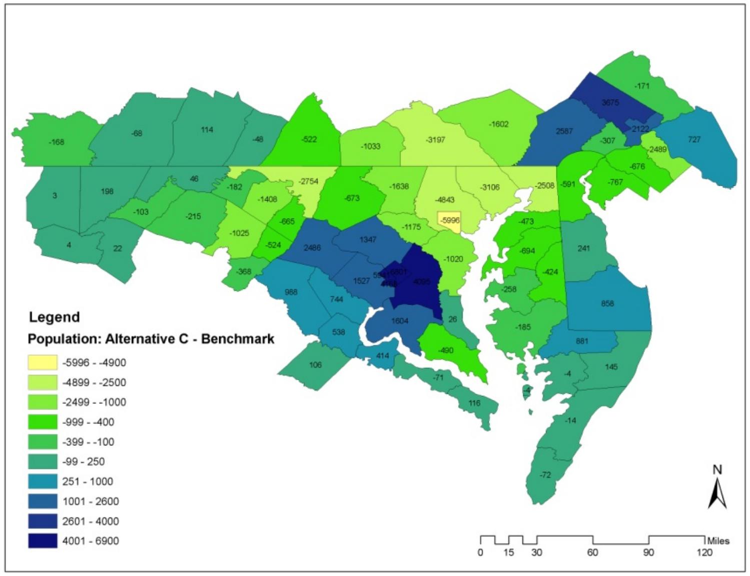


Figure 10. Differences in Populaiton between Base and Alternatives A, B & C

From Top left

(a) Differnce between population allocation with both "employment access" variable on households and CGS output of STEMS (Alternative A) from the Base

(b) Differnce between population allocation with "employment access" variable on households (Alternative B) from the Base

(c) Differnce between population allocation with CGS output of STEMS" (Alternative C) from the Base

Conclusions and Further Work

At this stage, there are no feedbacks between the county allocation models and the US and state economy. Furthermore, the population forecasts in the LIFT and STEMS are treated exogenously which drive the labor force rates which then drive the productivity to generate outputs for the economy in various sectors. While this is not a serious limitation at the national level, migration with in the nation if presumed to follow the economy rather than driving it at a state and local level then STEMS need to be much more sensitive to the demographics.

It is also unclear at this stage, if the ad hoc nature of access variable used in reallocating the households and therefore employment is verifiable. Such verification entails finding a situation in which all the assumptions of the scenarios are satisfied or building a model in which the structure of the equations do not change under all scenarios. Such exercise is not only practically infeasible, but theoretically implausible. Scenario construction should entail building plausible forecasts given uncertainties to the inputs of the model, but also acknowledging the uncertainties with regards to the structures of the model.

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