# Consumption Equations in *IdLift*: Extension and Revision

Consumption by far is the largest component of final demand. Hence, consumption equations perhaps are second in importance only to the fundamental input/output identities in the *IdLift* model. It then is appropriate that they receive great attention in terms of data preparation, estimation, and simulation and forecasting. With this in mind, the existing consumption equations, which already comprise the most elegant system in the model, have been extended and revised.

This paper is composed of three parts. The first describes revision of the adult equivalency weights used in earlier systems. The second describes an extension of earlier versions and estimation of the resulting system of equations. The final section includes forecasts and simulations using the new equations.

## Adult Equivalency Weights in PADS

The system of consumption equations currently used in *IdLift* was introduced first by Almon in 1979. That model was employed and extended several times (Devine (1983), Chao (1995), and Janoska (1996)) before Almon announced an improved version in 1996 called the Perhaps Adequate Demand System (PADS). The existing model, as presented here, is a collection of the techniques introduced in these papers. Bardazzi and Barnabani (2001) constructed and estimated a similar model for Italy.

Estimation of the Perhaps Adequate Demand System (PADS) is undertaken in two stages. In the first stage, cross sectional consumption data is regressed on income, demographic, and age group variables. The 10 demographic variables are

ncent	Region = North Central States
south	Region = Southern States
west	Region = Western States
college	Education of Household Head = College
twoy	Working Status of Spouse = Employed
fs1	Family Size = 1
fs2	Family Size = 2
fs5	Family Size $\geq 5$
head1	Age of Head of Household < 35
head2	Age of Head of Household > 55.

These variables enter the following equations:

$$C_{i}^{*} = \left(a_{i} + \sum_{k=1}^{K} b_{i,k} Y_{k} + \sum_{l=1}^{L} d_{i,l} D_{l}\right) \left(\sum_{g=1}^{G} w_{i,g} n_{g}\right)$$

#### where:

 $C_i^*$  = household consumption expenditures for good i

 $Y_k$  = levels of per-capita income in income bracket k

 $D_1$  = dummy variable used to show membership in the  $l^{th}$  demographic group

 $n_g$  = number of household members in age category g

w<sub>g</sub> = adult equivalency weights (estimated parameters)

K = the number of income groups

L = the number of demographic categories

G = the number of age groups

a, b, d = estimated parameters

The dependent variable, "Cstar," is the product of two functions. The first includes a constant, a piecewise-linear Engle curve, and a weighted sum of demographic dummy variables. The second function is a weighted sum of family members; it allows unique weights to be assigned to members of each age group, where weights for age group 31-40 are normalized to unity. If we divide both sides of the equation by the terms in the second set of parentheses, we see that this method is a generalization of per-capita estimation techniques. For convenience, these weighted sums of age variables shall be called "populs," and consumption categories divided by their respective "populs" are called "per popul" consumption categories; note the similarity to per capita consumption.

Devine (1983) and Chao (1995) estimated the above equations. Until a new version of these equations is complete, we are left to make the best of these estimates. Unfortunately, the data used by Devine are more than 20 years old. New products have been introduced, and older folks now use gadgets unavailable to or ignored by the preceding generation. The data Chao used is much newer, and it has been used in *IdLift* almost exclusively. Most of the parameters provided by Chao do not violate theoretical priors and seem to yield reasonable simulations. An unfortunate exception is the set of estimated adult equivalency weights. Theory suggests that for any good, the sequence of weights across age groups should be fairly smooth. For example, young children consume little of the first product, Meat. The next group, ages 6-15, consumes more, and so this group should receive a higher adult equivalency weight. The following group, teens and young adults, should receive still a higher weight, and so on. This sequence of weights may peak and then decline for older age groups, but almost certainly the sequence should be smooth.

Unfortunately, Chao's estimates are far from smooth for many products. Many such estimates are shown in Appendix 1. These graphs titled *IdLift* display the weights used most recently in *IdLift*; most are taken from Chao's work, but some have been altered or taken from other estimates. An example of problematic estimates are those for Product 90: Foreign travel and purchases abroad. According to the estimates, children of ages under six account for a great deal of foreign travel, but children of ages six to fifteen account for very little. Similarly, adults of ages 21 to 30 travel a great deal, but adults of ages 31 to 40 travel very little. Finally, adults of ages 41 to 65 travel extensively, but adults over 65 travel little. Perhaps a plausible story can explain this qualitative pattern, but the extreme fluctuations seem unrealistic. Also, the large weights given to the youngest age group seem improbable. Consider the implied effect of aging of a large cohort. In the years following birth, foreign expenditures rise dramatically but then

fall just as rapidly when the cohort passes age seven. Holding all else constant, expenditures climb again after age 15 but peak when they reach age 30. Expenditures fall again as the cohort reaches its fourth decade, then climb again only to drop precipitously upon retirement. Hence, predicted demand swings wildly as the population segments age. Again, we expect differences among the age groups, but those differences generally should follow a smooth curve across age groups.

As will be seen in the next section, the predictions of these equations are not used directly to estimate consumption. Instead, an affine transformation of these first stage estimates enters the second stage in addition to its first difference. Hence, we have some latitude to adjust the weights without reestimating the entire equation. Any such modification of the parameters is crude manipulation and in many ways undesirable. However, it may yield improvements over another system with flawed parameter estimates. Hence, we examine a system with modified adult equivalency weights. The weights are adjusted to yield curves that are relatively smooth and conform to theoretical priors. Modified weights are graphed as *NewLift*. In the modified system, children under age 16 account for little of the expenditures for Product 90: Foreign travel. Weights increase monotonically until ages 31 to 40, fall slightly for ages 41 to 65, and then rise again in retirement years.

The process of choosing weights was rather ad hoc, but generally one of three alternatives was chosen: the Chao weights, the Devine weights, or the average of Chao and Devine weights. The average seemed superior in some cases primarily because it tended to be smooth and it avoided extreme values that crept into the estimates. Some weights were modified regardless of which set was chosen. Negative weights, for example, were made nonnegative in sets of weights that otherwise seemed reasonable. In the food group (Products 1 to 14), the Chao weights were adopted except for ages 41 to 50. Since the estimate is very large for this age group, a substitute was calculated as the mean of the weights for adjacent groups. Similarly, Chao weights were used for Product 60: New autos, except for the last weight. The estimated weight is very large, so a smaller weight is used instead. Devine weights are used for Product 18: Mens' clothing, and the average of Chao and Devine weights are used for Product 16: Footwear.

A new set of weights were calculated at Inforum by Ralph Monaco and employed for health care products (Products 45 to 51). These weights were calculated from 1993 NHIS data supplied by HCFA. The data include the number of visits and the average cost per visit for each age group. The number of visits was multiplied by the average cost to yield total costs for each age group. The results were normalized by the value for ages 31 to 40, yielding costs for each age group relative to costs for adults between ages 31 and 40. The equations described above are

$$AEW_{i} = \frac{Cost_{AgeGroup(i)}}{Cost_{AgeGroup(31-40)}} = \frac{Visits_{AgeGroup(i)} * Avg.CostPerVisit_{AgeGroup(i)}}{Visits_{AgeGroup(31-40)}} * Avg.CostPerVisit_{AgeGroup(31-40)}.$$

Differences between these calculations and the estimated parameters are substantial in some cases. For Product 51: Nursing homes, the Chao weights increase very little as age increases. Monaco weights increase slightly for ages 41 to 50, increase significantly for ages 51 to 65, and rise dramatically for ages 66 to 99. Clearly, this latter pattern is more realistic. On the other

hand, the weights for Product 45: Drug preparations and sundries are very similar, lending credibility to adoption of Monaco weights.

In summary, *ad hoc* alterations of adult equivalency weights have been introduced temporarily until satisfactory estimates can be made from recent data. Clearly, this modification nullifies any claims that the original estimates were unbiased or that they meet any other such qualities that are of great interest to econometricians. As will be seen shortly, these equations are the first of two stages needed to calculate consumption. The first stage thus can be viewed as construction of a demand index that then is employed in the second stage to predict consumption. With this in mind, the hope that substitute parameters can yield improved fit seems more reasonable. Still, these measures are troublesome; forthcoming work by Li Ding at Inforum promises real improvement.

## The Consumption Functions

The first stage of estimation ignored price effects and dynamics. These are introduced in the second stage, which is estimated with time series data. The consumption functions are

$$x_i(t) = \left(\alpha_i + \beta_i \frac{y(t)}{P(t)} + \sum_{k=1}^{K_i} \theta_{i,k} T_{i,k}\right) \prod_{n=1}^{N} p_n^{\delta_{i,n}}$$

$$P = \prod_{n=1}^{N} p_n^{s_n}$$

where  $x_i(t)$  is per capita consumption of product i in period t;  $\alpha$ ,  $\beta$ ,  $\delta$ , and  $\theta$  are parameters; y(t) is a measure of nominal per capita income or expenditures; and T are  $K_i$  additional variables important to product i.  $p_n$  is the price of product n and is equal to unity in an arbitrary the base year.  $s_n$  is the budget share of product n in the same base period; and P is the overall consumer price index. The estimated form of the model is

$$x_i(t) = \left(\alpha_i + \beta_i \frac{C_i^*(t)}{P(t)} + \phi_i \Delta \left[\frac{C_i^*(t)}{P(t)}\right] + \sum_{k=1}^{K_i} \theta_{i,k} T_{i,k} \left(\frac{p_i}{P}\right)^{\lambda_i} \prod_{n=1}^{N} \left(\frac{p_i}{p_n}\right)^{-\lambda_n s_n} \left(\frac{p_i}{p_G}\right)^{-\mu_G} \left(\frac{p_i}{p_g}\right)^{-\nu_g} \right)$$

where:

 $x_i$  = per "popul" consumption of product i

 $C_i^* = \text{expenditure estimates from the first stage}$ 

 $p_G$  = the average price index of group G

 $p_g$  = the average price index of subgroup g

 $\lambda_i$  = the individual good price response parameter

 $\mu_G$  = the group price response parameter

 $v_g$  = the subgroup price response parameter

 $\Delta$  is the first-difference operator. Remaining parameters and variables are described above. In this form, consumption products have been organized into groups and subgroups to reduce the

number of parameters, and symmetry of price effects has been imposed. Almon (1996) derives and describes these equations, and Bardazzi and Barnabani (2001) offer an alternative description. "Cstar" estimates of consumption expenditures are used in place of disposable income, total consumption expenditures, or another measure of spending. The primary purpose of this technique is to capture demographic and income distribution effects. Inforum uses a two-stage approach in its *LIFT* model in a system very similar to that of Bardazzi and Barnabani. Almon (1996) estimates a single-stage system using total consumption expenditures instead of Cstar.

In previous versions of *PADS*, there was a single linear term T in addition to the Cstar terms. Almost always, the single term was a linear time trend. For some products, variables other than price, income, demographics, and the passage of time are important. Interest rates, for example, may be important to demand for durable goods and for other products purchased on credit. Other important variables include stocks of durable consumption goods, transfer payments, construction spending, and housing stock. Dummy variables also may be constructed to incorporate information not captured in prices or in other variables. Expectations of oil prices, for example, may be important for estimating demand for automobiles and other energy-intensive products.

The ability to estimate parameters for such variables greatly extends the flexibility of the basic model. However, it remains the responsibility of the model builder to determine which, if any, additional factors are important. In addition, the model builder must provide guidance, in the form of "soft" constraints (see Almon 1996), to obtain a parameter set that conforms to economic theory and that produces reasonable simulations and forecasts. This step is quite difficult, and the model builder often must choose between quality of fit and forecasting performance. Results for this paper are mixed, with estimates for some products showing clear improvement while others show no improvement with the addition of extra variables. In the end, relatively few products are estimated with additional terms.

Appendix 2 displays two sets of graphs. The first displays the data and estimates for the 92 consumption products modeled by *IdLift*; the units are "per popul." The second set shows forecasts and simulations using these equations; results of these simulations are presented in the following section. Appendix 3 presents a list of products and the extra independent variables (*T* in Equations 1.3 and 1.4) for each good.

### Estimation of the Consumption Functions

Estimation consists of several steps. First, the model builder must determine which, if any, variables in addition to time, income, and prices are important for specific products. Following estimation, the parameters must be reviewed. For reasonable performance in a larger (general equilibrium) model, the parameters should agree qualitatively with economic theory. In addition, the parameters should seem qualitatively reasonable. For example, time effects should not dominate to the exclusion of income effects. When economic theory is violated or other problems are apparent, soft constraints must be introduced; see Almon (1996) for details. Once reasonable fits and parameters have been achieved, the parameters are inserted into a general

equilibrium model like *IdLift*. When the model has been solved, the predictions for consumption products again are reviewed. Sometimes, additional use of soft constraints is required, typically to reign in explosive growth or to reduce feedback effects from the extra variables. In such cases, the parameters again are estimated with the new set of constraints, and the model is solved again.

Clearly, there is a tradeoff between fit and forecasting or simulation performance. Optimal fit is achieved with no constraints. Unfortunately, many income elasticities then will be negative and price elasticities positive; clearly, these violate economic theory. In a forecast with income (or Cstars) increasing, demand will fall for those products. Similarly, demand will rise with prices. Whether the "faulty" parameter estimates result from inadequate¹ or imperfect data, collinearity, model misspecification, or other problems, they will cause problems if the model builder fails to impose priors. In many cases, many constraints must be imposed at the expense of the fit. For the fits and forecasts presented in Appendix 2, relatively more weight was given to simulation performance than to data fitting. Consequently, the fits are relatively poor for some products even though the equations are able to achieve very good fits for most products when the constraints are relaxed.

Similarly, some extra variables had to be discarded because they created feedback problems in the *IdLift*. For example, the stock of automobiles (constructed from the sale of Product 60: New cars) is used to estimate demand for Product 61: Used cars and Product 63: Tires, tubes, accessories, and parts. It is not used to estimate Product 60: New cars because of feedback problems. Essentially, the stock of cars becomes an autoregressive term for Product 60. Two problems typically arise: the autoregressive terms tend to dominate other variables in the equation, and forecast errors are propagated forward. The first is an estimation problem; it can be controlled, to some extent, with soft constraints. The second is a serious problem for long-term forecasting. Forecast errors in new car sales become embedded in the forecast of automobile stocks. This forecast of stocks, together with its forecast errors, is used to produce the next period of new car sales. The prediction of new car sales may explode or simply behave erratically; almost certainly, the inclusion of "autoregressive" terms like automobile stocks will cause problems in forecasting new car sales. On the other hand, forecast errors do not compound so quickly when using auto stocks, computed from Product 60, to predict sales of used car, tires, and parts.

Other variables contribute to PCE too little for their inclusion to improve prediction. For example, food stamps and other transfer payments may affect food purchases directly. However, food stamps contribute an average of only 0.002 percent to PCE food sectors. It seems that the effect of these transfers on PCE is too slight to justify inclusion in the equation even if its inclusion appears to improve the fit of the data.

Perhaps the strongest support for expanding the equations to take on additional variable comes from durable goods. Product 28: Furniture and Product 29: Kitchen and household appliances responded very favorably to the inclusion of interest rates. As expected, the signs on the interest rate parameters are negative and robust to other changes in the system. Without

<sup>&</sup>lt;sup>1</sup> Data employed for this project extend from 1971 to 2000 at annual frequency. Forecasts and simulations begin in 2001 for most series, although forecasts begin earlier for some variables due to lags in data availability.

interest rates, the equation captures the trends but fails too capture the significant market fluctuations. With the addition of interest rates, the equation captures both the trends and the business cycles. The equations for these two products and Product 31: Floor coverings, Product 34: Semi-durable household furnishings, and Product 35: Cleaning, lighting, and paper supplies also include a residential construction variable. The wide swings in residential construction, which often closely track the business cycle, seem to explain much of the similar swings in these durable goods.

A related measure, stock of residential structures, is used to estimate demand for energy and water and sanitary services. (Due to possibly unrelated problems, the Product 37: Electricity remains in its original form for this version.) Intuition suggests that housing stock plays an important role for these products, and their inclusion may improve the estimates. Unfortunately, for reasons described above, the parameters could not be estimated reliably. Soft constraints were used to ensure the parameters were slightly positive.

Hospital and medical insurance benefits were included for health care products (Products 45-52). In at least some cases, fit of the data improves significantly and most parameters were positive, as expected. Soft constraints were used to reduce the magnitude of the parameters, but some feedback problems may exist since insurance benefits also are endogenous. Should significant problems become evident, transfers may be eliminated from these equations in future versions.

A crude estimate of expected gasoline prices was constructed under the assumption of adaptive expectations. This measure was included in New automobiles, Used automobiles, Other motor vehicles, and Bicycles and motorcycles. Because the variable is constructed from lagged price data, it contains information that is not available in current prices. If the estimates are believable, then consumers buy more new cars when gasoline prices are expected to rise. At the same time, they buy fewer trucks and used cars. This seems plausible if the new cars tend to be more efficient than the trucks and used cars. The inclusion of expected gasoline prices improved the fit for Product 76: Bicycles and motorcycles dramatically. Two problems exist with the estimate. First, the parameter is negative; high gas prices should encourage substitution of bicycles and motorcycles for cars and trucks. Second, the magnitude of the parameter is too great; demand responds too strongly to gas price shocks. Under simulations with significant gas price shocks, demand for bicycles and motorcycles responds more strongly than any other product. Almost certainly, this does not reflect reality. Perhaps the constructed expectations mimic an omitted variable, and expected gas prices play little role and should be dropped. The parameter at least should be made smaller in magnitude and perhaps positive through use of soft constraints.

Two educational products, Higher education and Other education and research, and Religious and welfare products are estimated with construction of educational and religious facilities, respectively. Problems with feedback were countered with soft constraints; the efficacy of this remedy is questionable. The forecasts seem reasonable, but other simulations must be constructed to provide additional support.

Other variables are included also, and many were tried that are not included in this version. Effects of some variables clearly are important for estimating consumption. Unfortunately, estimation is made more ambiguous and difficult by adding other terms that seem equally to be important. Perhaps the primary contribution of this project is the modification of the estimation software that now allows model builders to easily test extensions of the basic consumption system. The set of variables that may affect consumption has just begun to be examined in this framework. Surely the greatest contributions still are undiscovered.

#### Simulations and Forecasts

Before concluding, let us examine the second set of graphs in Appendix 2. The model has been run to 2015 under three sets of assumptions: a base case, a scenario of high health care prices, and another with a shifted age distribution.

The base case maintains the assumptions of the Fall 2001 Inforum forecast. Primary deviations are the elimination of fixes for consumption products. (Fixes allow the model builder to control the forecast of certain variables; see, for example, Almon 1994.) The price of tobacco products now is set to grow 2 percent faster than the average for consumption goods. Under previous specifications, prices for tobacco products grew too slowly, causing improbable growth in demand. Other changes include data revisions for consumption and the correction of minor errors.

In the first simulation, prices for health care goods (Drug preparations and sundries, Ophthalmic and orthopedic equipment, Physicians, Dentists, Other professional medical, Hospitals, and Nursing homes) incur a permanent increase of 50% starting in 2001. The increase is relative to the model forecast without the fix (i.e. the base case). The savings rate decreases sharply and then moderates, but it remains negative throughout the forecast. Real GDP falls and maintains a lower level, but growth is diminished only in the first several years. Interest rates remain lower throughout the simulation, but they converge to rates in the base run. As expected, demand for most products fell as prices rose for these essential goods. Exceptions may indicate estimation problems, unexpected (but accurate) feedback effects, or the revelation of inferiority for certain goods. Example of such inferior goods may include Product 10: Other prepared food and public transportation products (Products 68, 69, 70, and 73). An example of feedback may be Product 45: Drug preparation and sundries. Although the price elasticity is negative and the price for this good increases, demand for this product increases. In the first several forecast periods, this phenomenon may be explained by rho adjustments; rho adjustments smooth the transition from historical data to the model forecast (see, for example, Almon 1994). However, although the effects of the adjustment diminish rapidly, demand remains greater that that in the base case. Another possible explanation for increased demand is that drugs are substituted for other health care products, and substitution effects overwhelm the effects of direct price increases. The increase in demand for Product 83: Clubs and fraternal organizations is likely an example of estimation problems. Perhaps folks like to gather to complain and commiserate about the high cost of health care; otherwise, increased demand seems unlikely.

The final simulation reported here includes a shift in the age distribution of consumers. Starting in 2001, the population of consumers aged 65 and under shrinks by 10 percent, and the

population of consumers above age 65 grows by 10 percent. This simulation reveals the effects of the adult equivalency weights.

According to the simulation, GDP, the savings rate, and interest rates are not very sensitive to the age distribution. It seems retirees no longer can maintain a diet high in Meat and Dairy products, Fats and oils, and Sugar and sweets. In fact, demand falls for all food products except Fish and seafood. It seems that wisdom comes with age, as demand for tobacco falls. Demand for energy products falls, but more so for natural gas than for electricity, fuel oil, and coal. Older folks seem more dependent on domestic services, but somewhat less dependent on telephone communications. As expected, the elderly spend more on health care products, and much more on nursing homes. It seems that pensions are spent on new cars rather than on repairs, and there is little need to rent or lease automobiles. Without the daily commute for retirees, demand for gas and oil drops, as do payments of tolls and auto insurance. Older folks don't seem to mind taxicabs or airlines, and they like busses, but they avoid mass transit and intercity rail when possible. Less time on the job allows more time for reading. grandparents undoubtedly buy Toys, dolls, and games for their grandchildren, it seems parents most often must pay the bill. In perhaps another display of increasing wisdom, demand for motorcycles and bicycles falls when average age increases. It seems electronic gizmos have yet to capture the attention of the aged, as demand for electronic entertainment, musical instruments, and home computers is reduced. However, grandparents enjoy live entertainment, sports, and movies nearly as much as their descendents. It seems the smaller number of school and college aged individuals requires less spending on education, especially for private lower education. Strangely, the simulation indicates that demand for clubs and fraternal organizations should fall with a higher proportion of elderly. If this seems implausible, it is a good reminder that these simulations merely display the result of our collection of data, assumptions, and estimates. The simulations do not offer a scientific test of demand responses under the various scenarios.

#### Conclusion

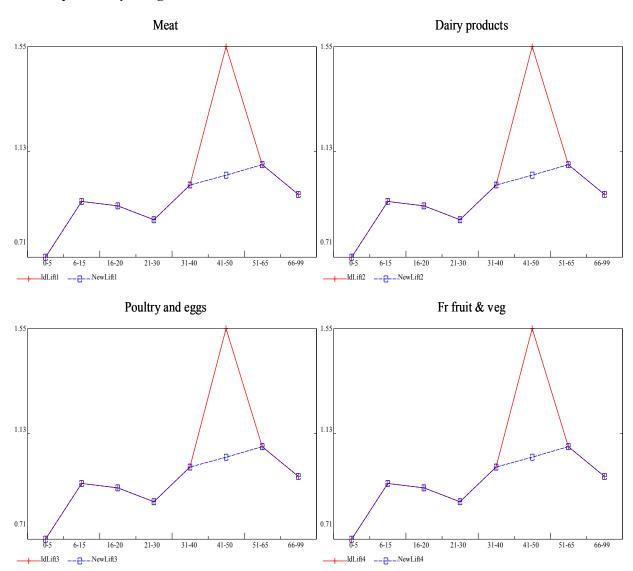
This revision of the PADS system of consumption equations offers some improvements to and extensions of the earlier equations. While this project addresses certain problems with the previous system, suitable solutions likely must wait until completion another research project at Inforum. For example, that project will estimate adult equivalency weights with recent cross sectional data, making unnecessary the *ad hoc* adjustments described in this paper. Hopefully, additional variables that are important to demand will become obvious. Nevertheless, we now have a set of several variables, including interest rates and residential construction, that significantly improve estimation of some consumption products. Improvement of other estimates has proven challenging, and much remains to be done.

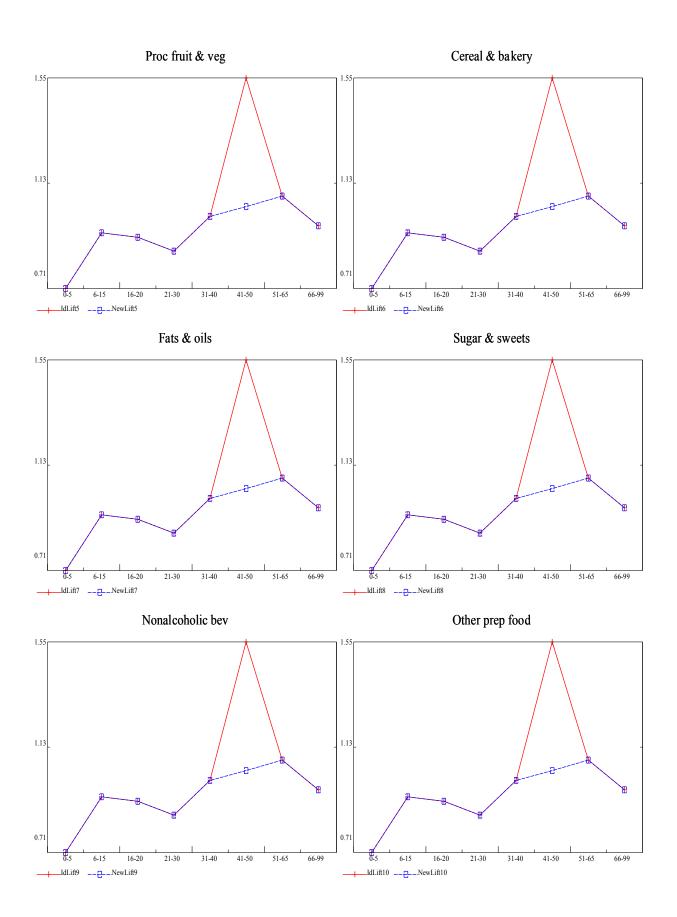
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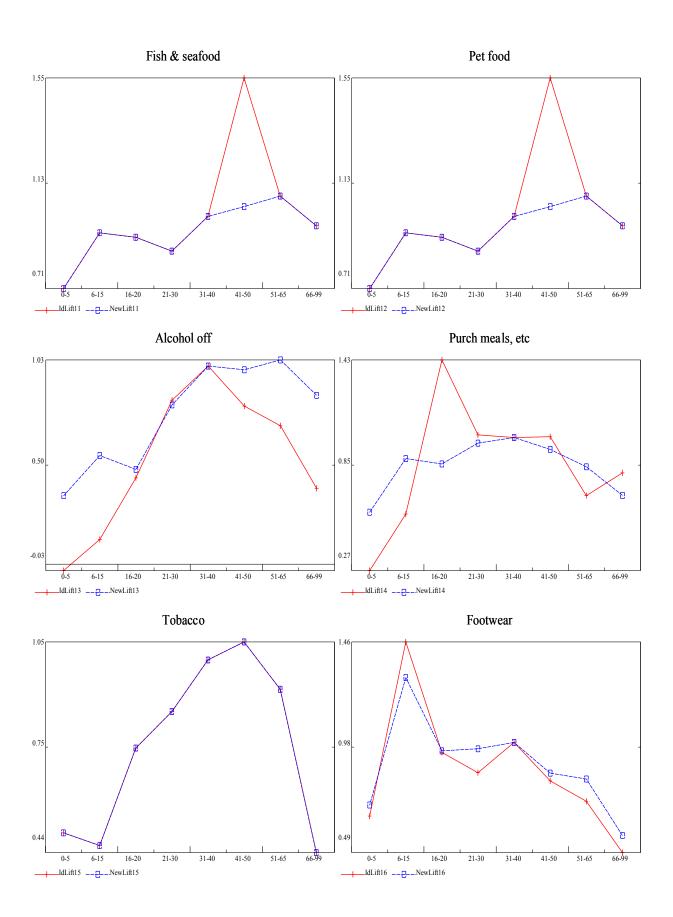
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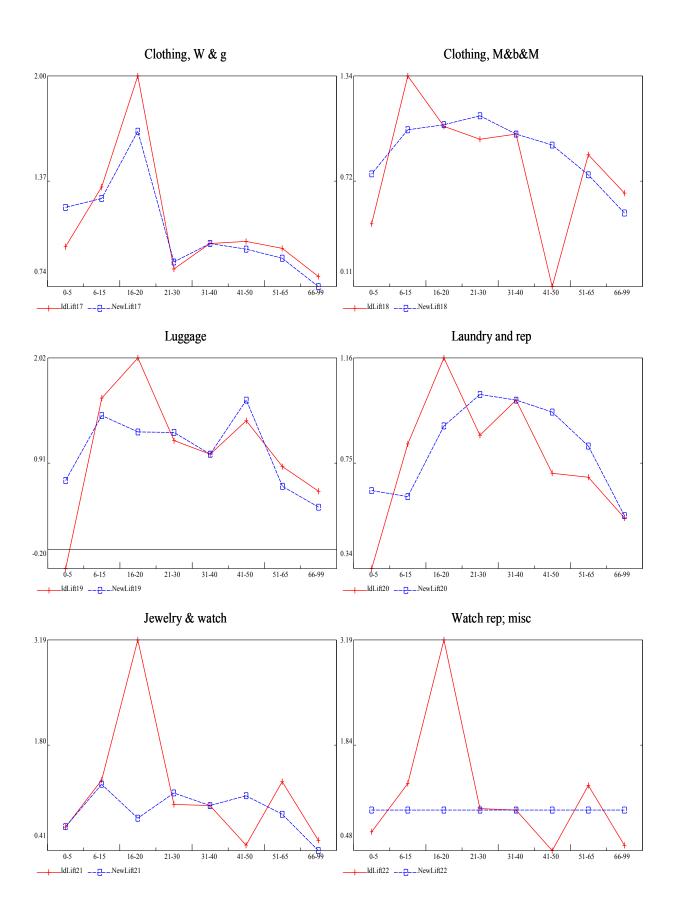
Appendix 1

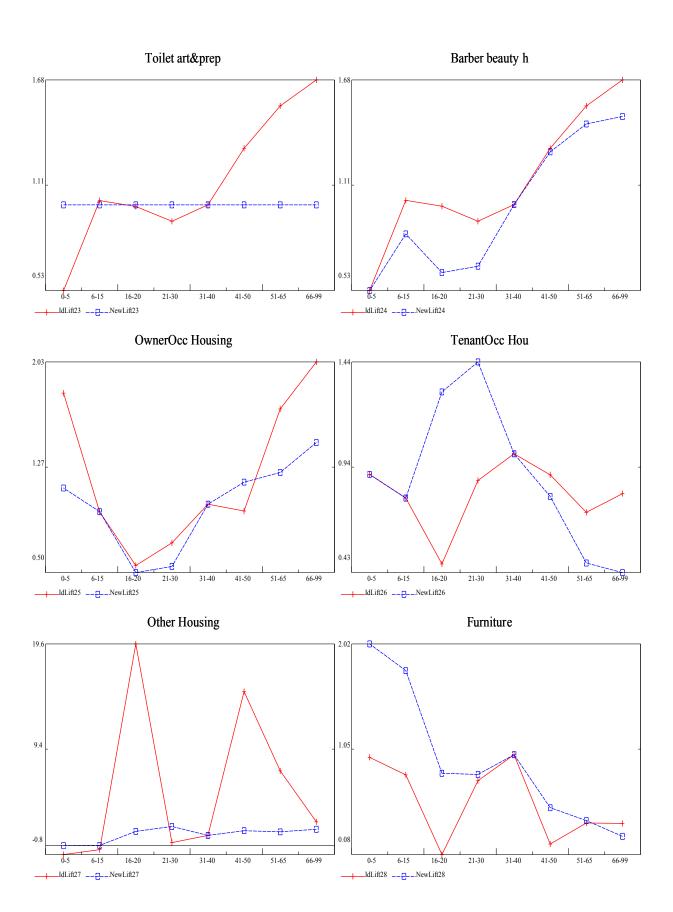
Adult Equivalency Weights.

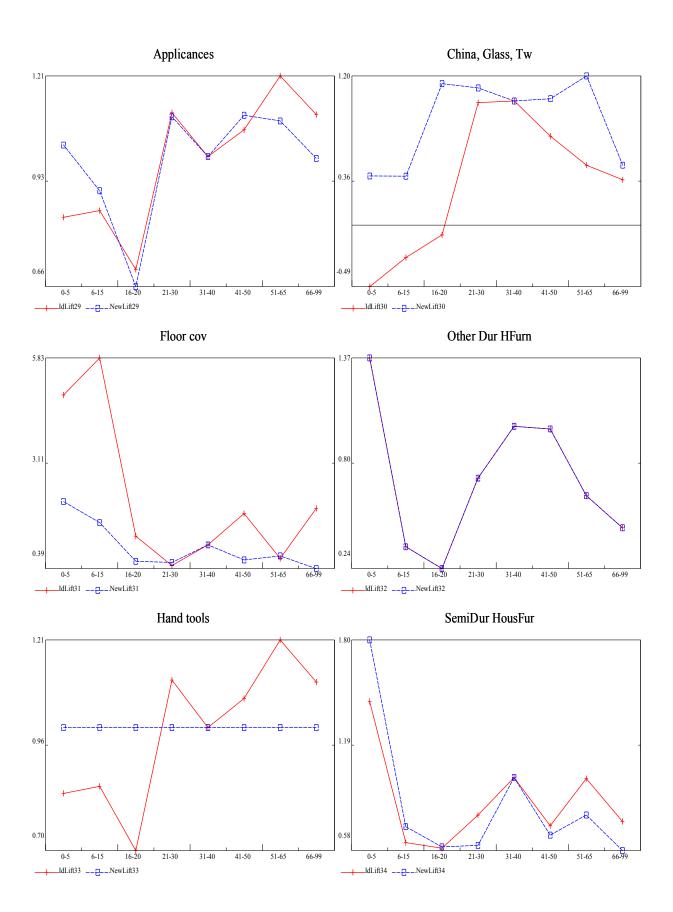


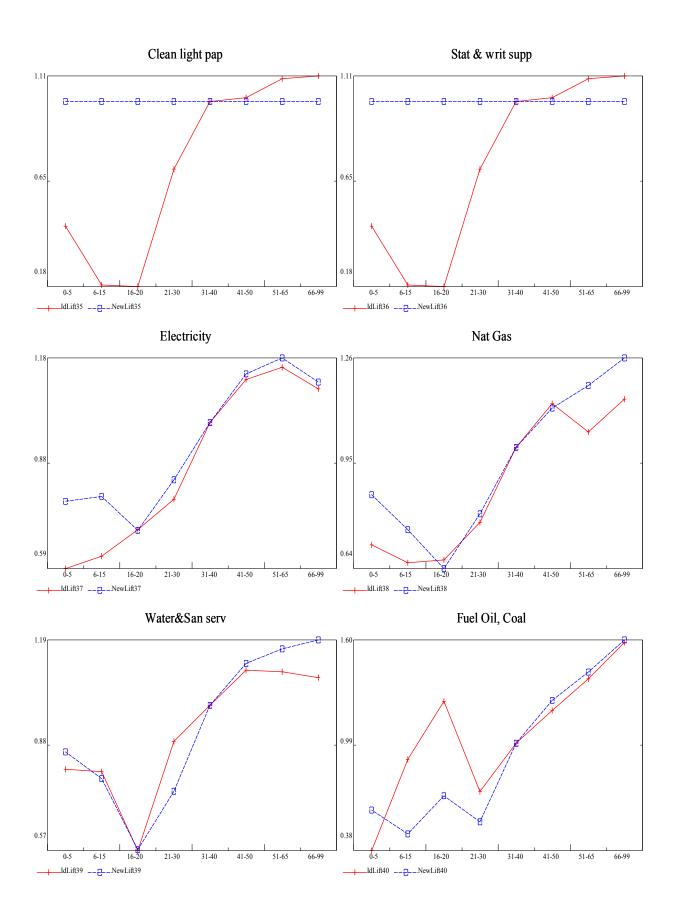


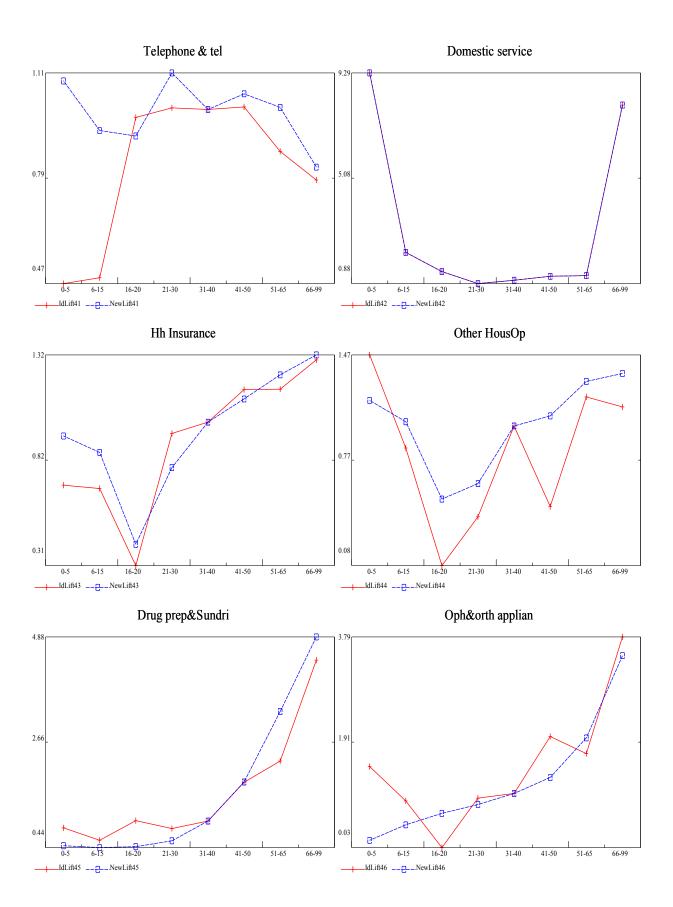


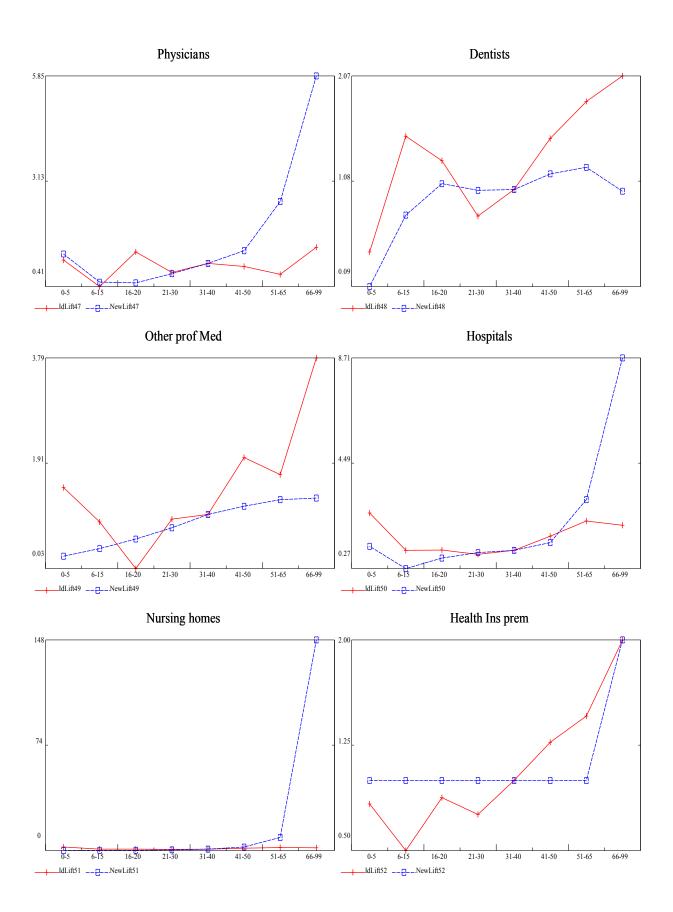


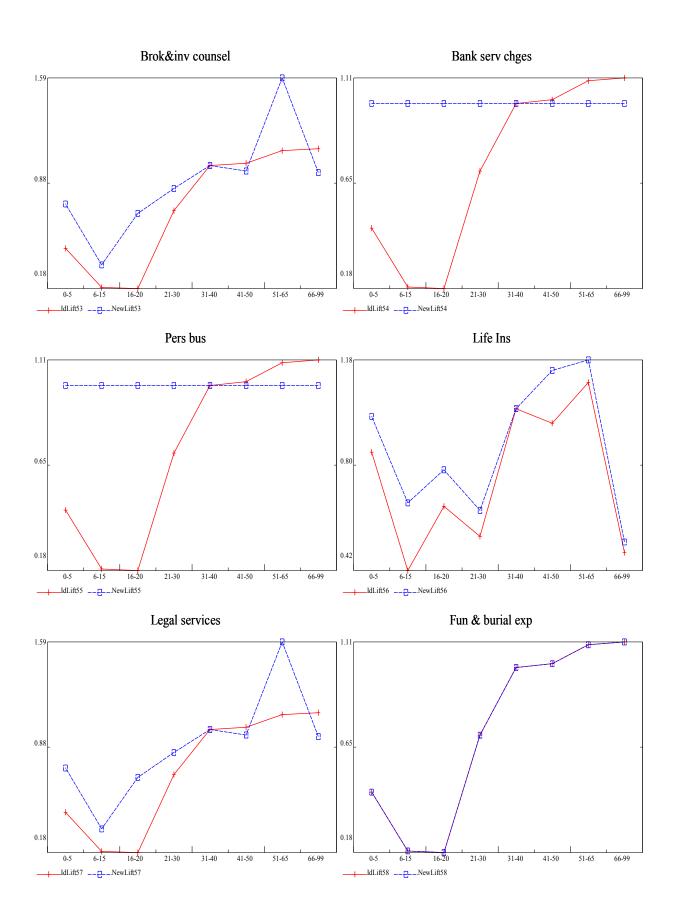


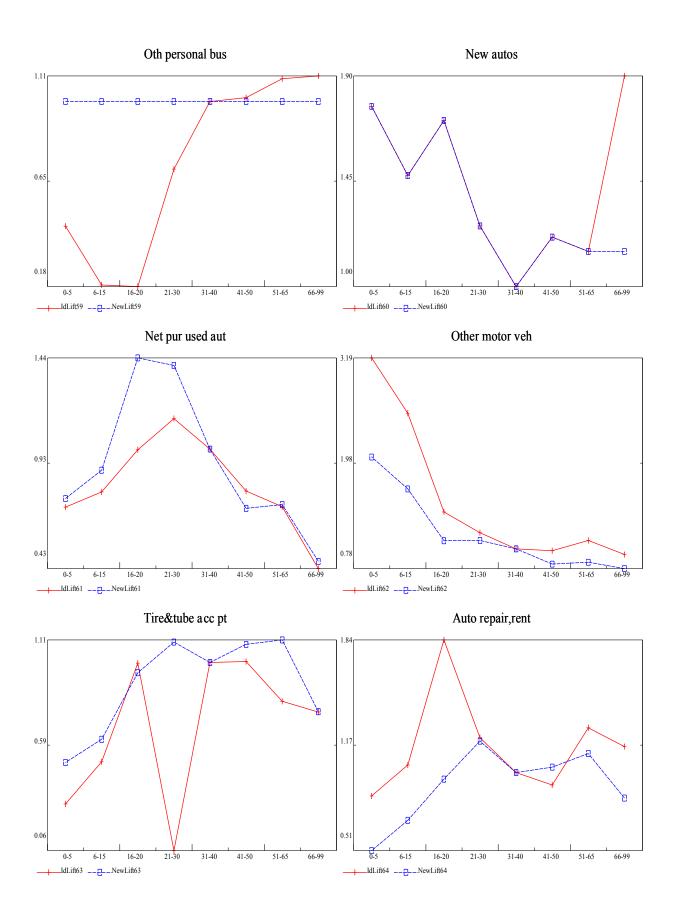


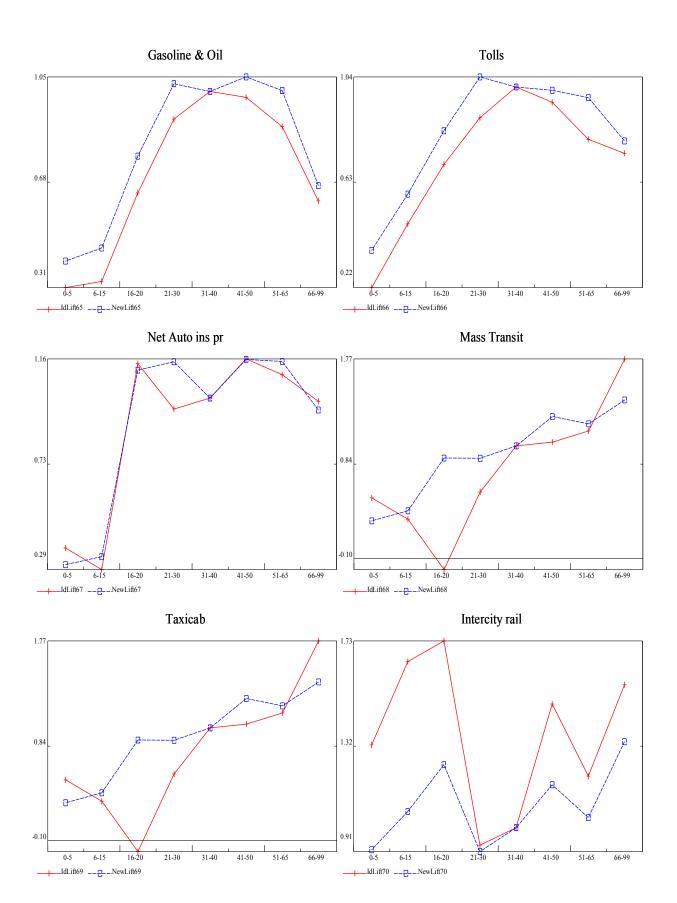


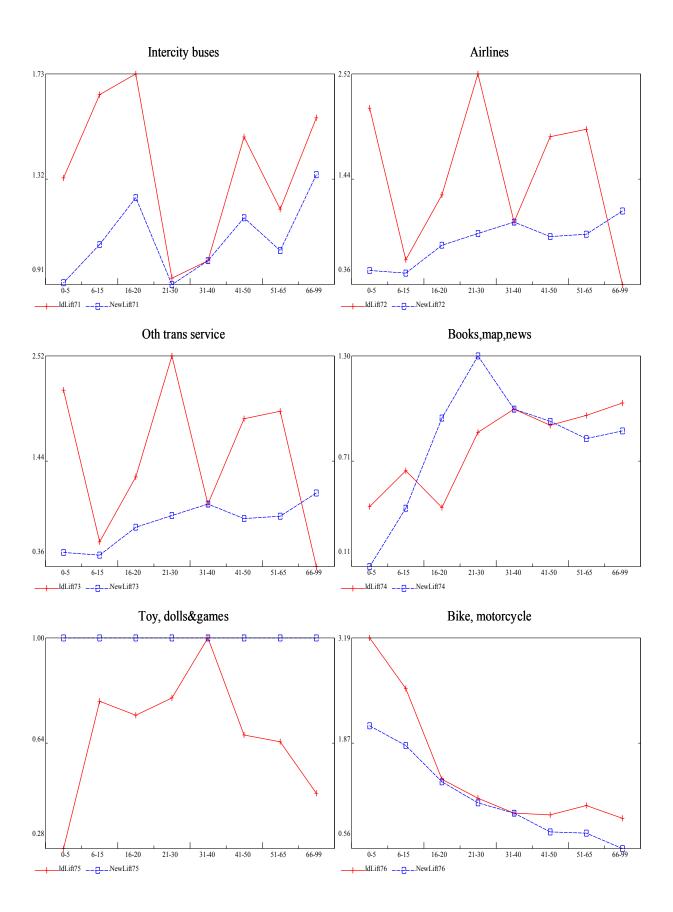


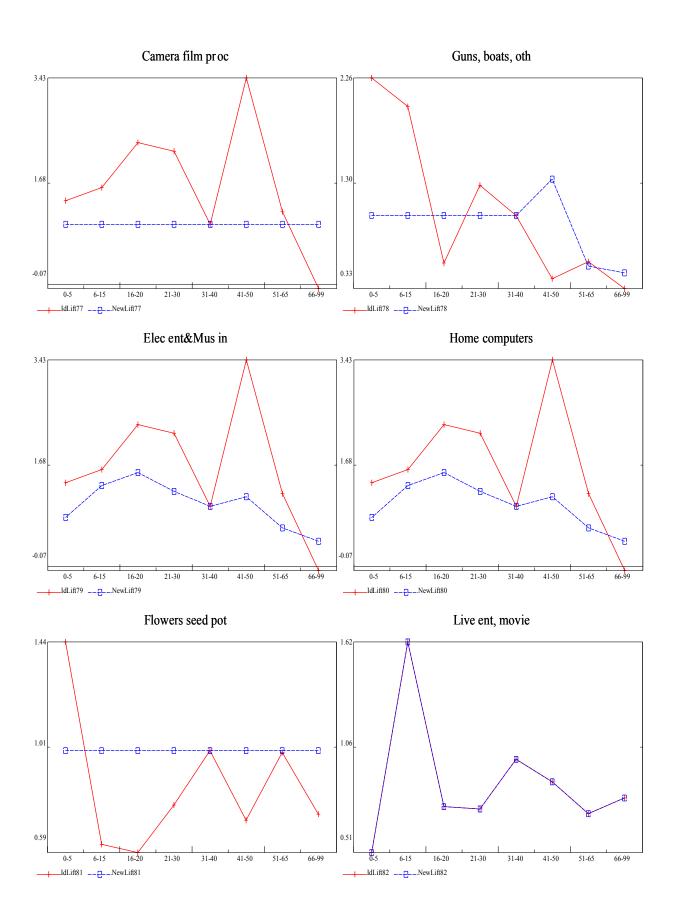


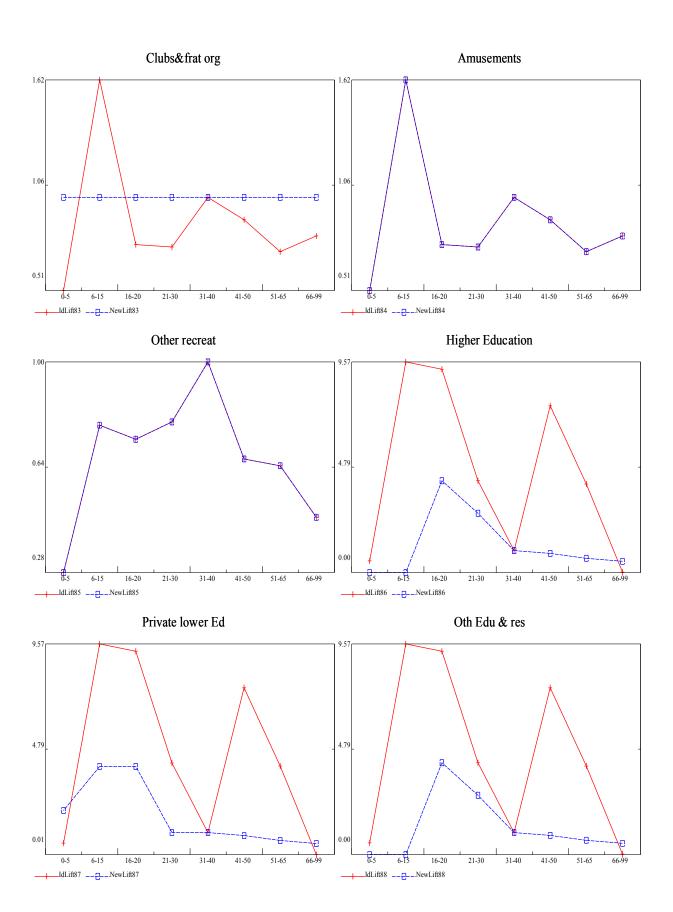


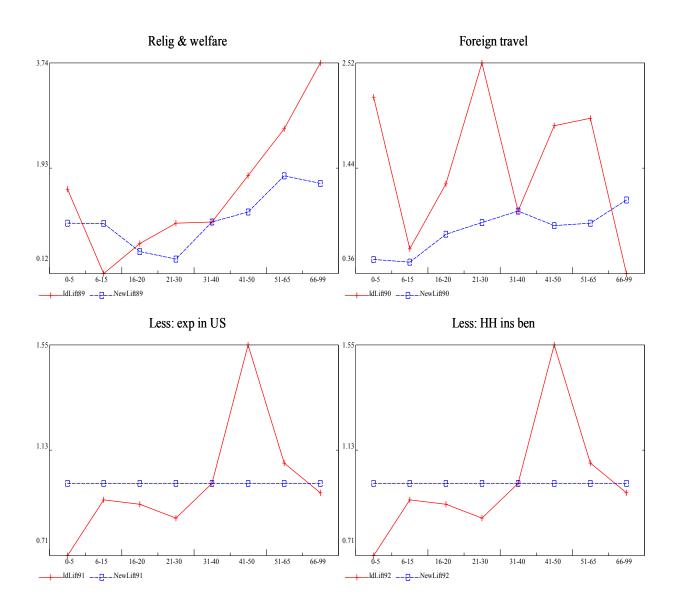










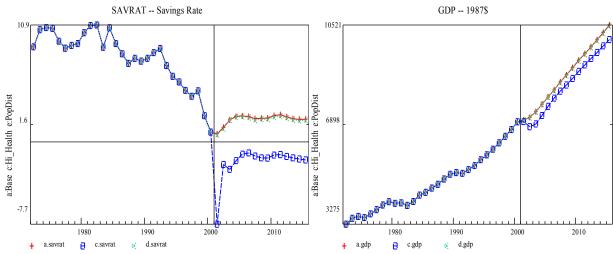


# Appendix 2

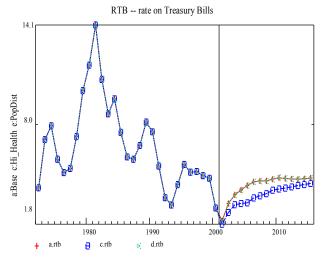
Fits, forecasts, and simulations.

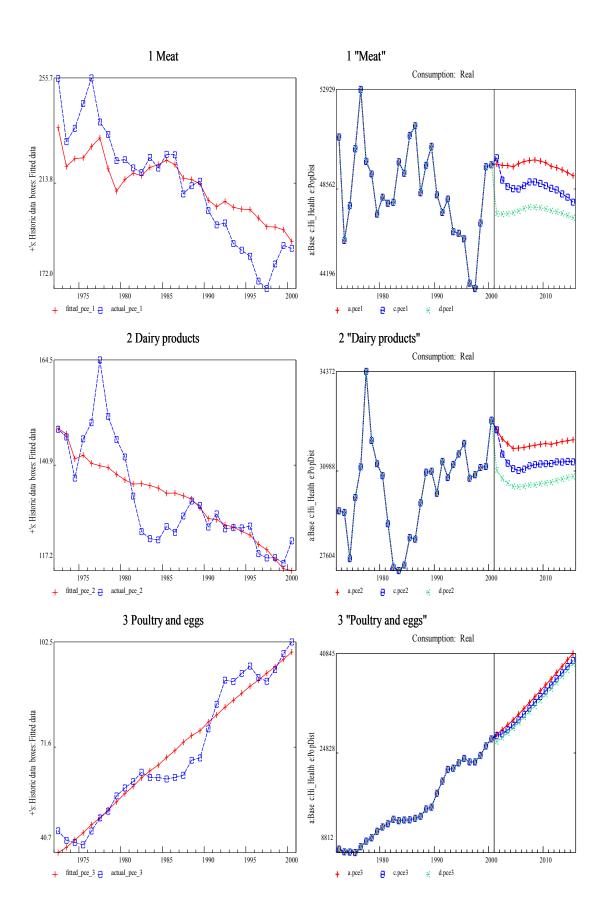
# Macro Forecasts with New Consumption Equations

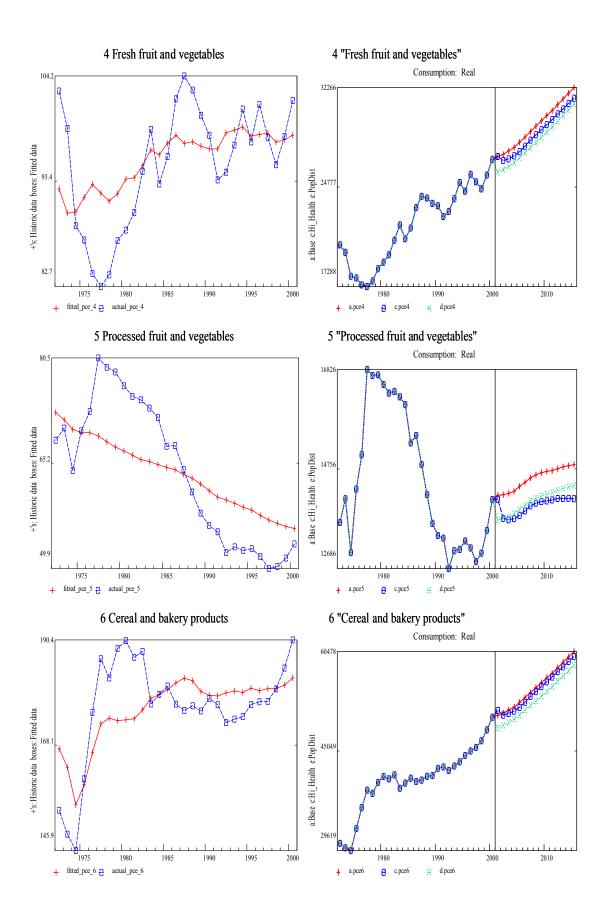
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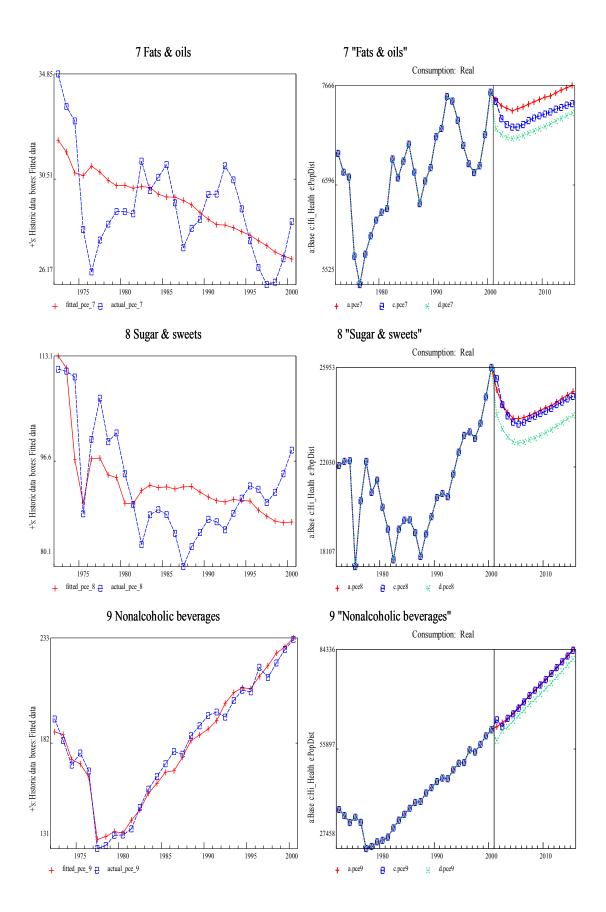


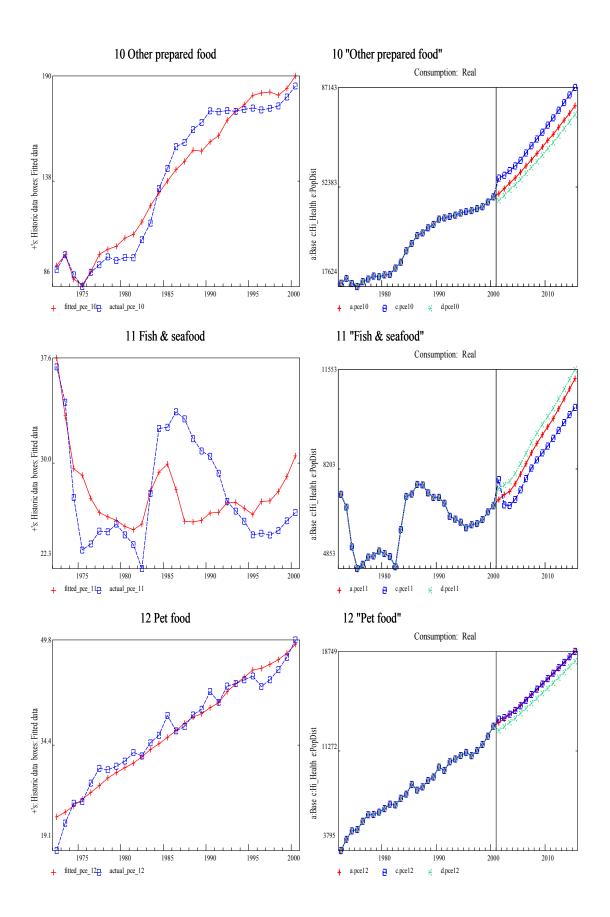
## Macro Forecasts with New Consumption Equations

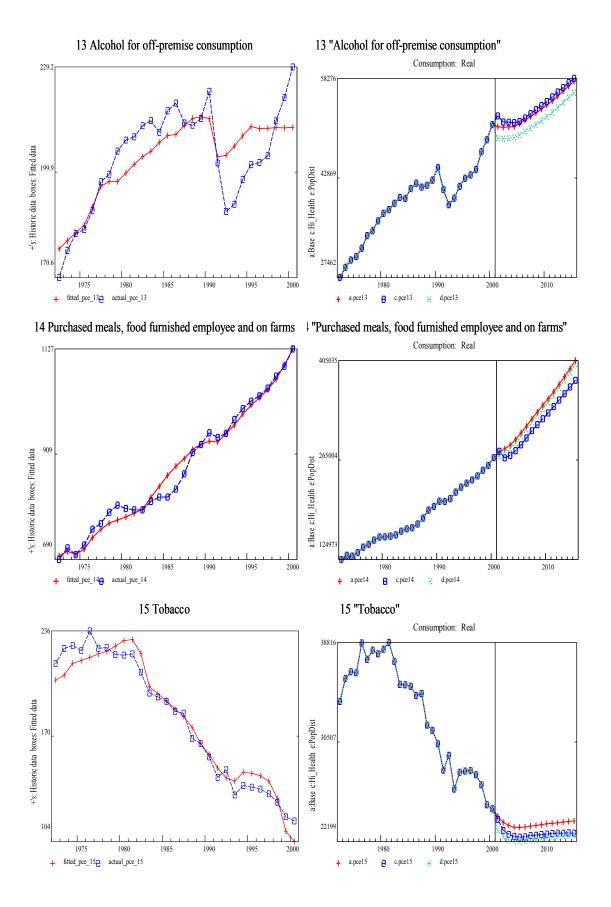


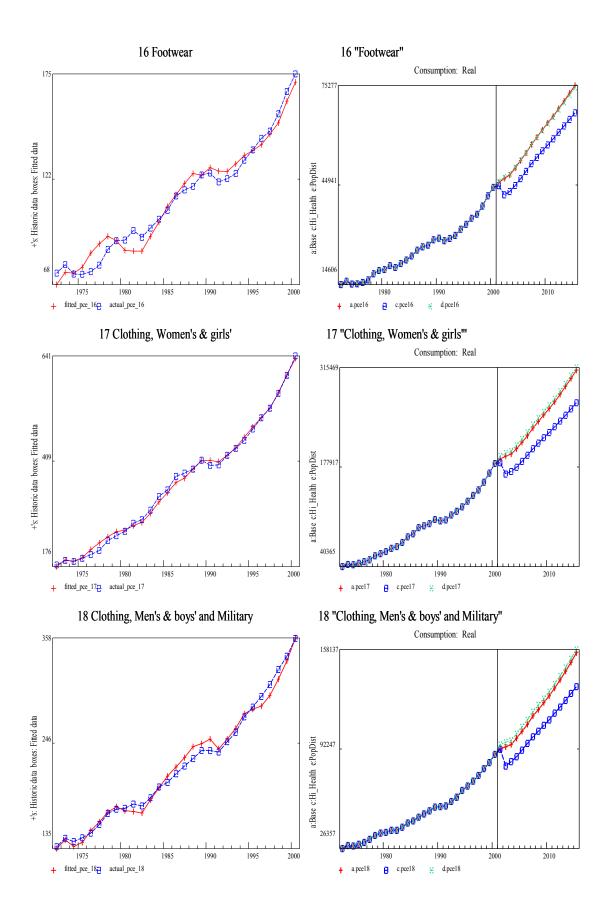


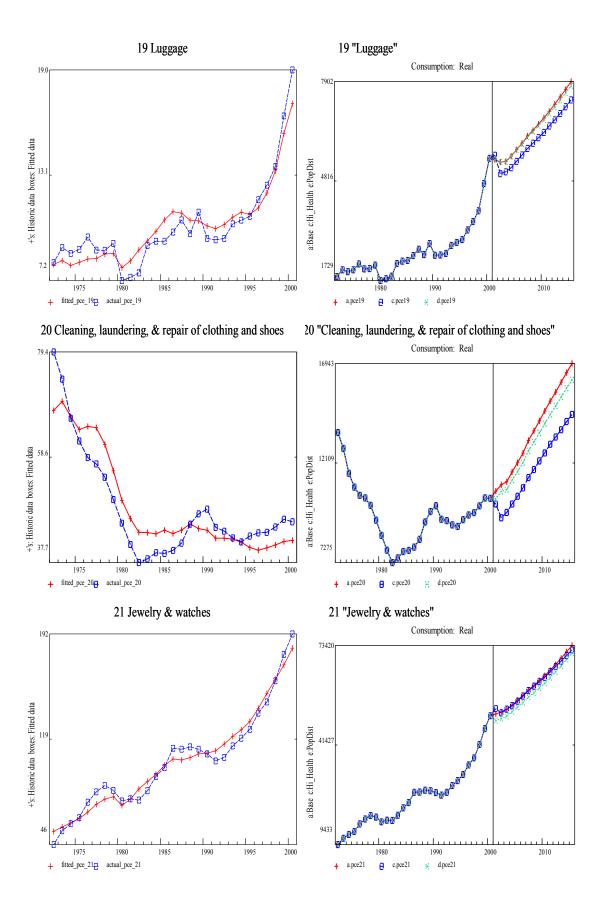


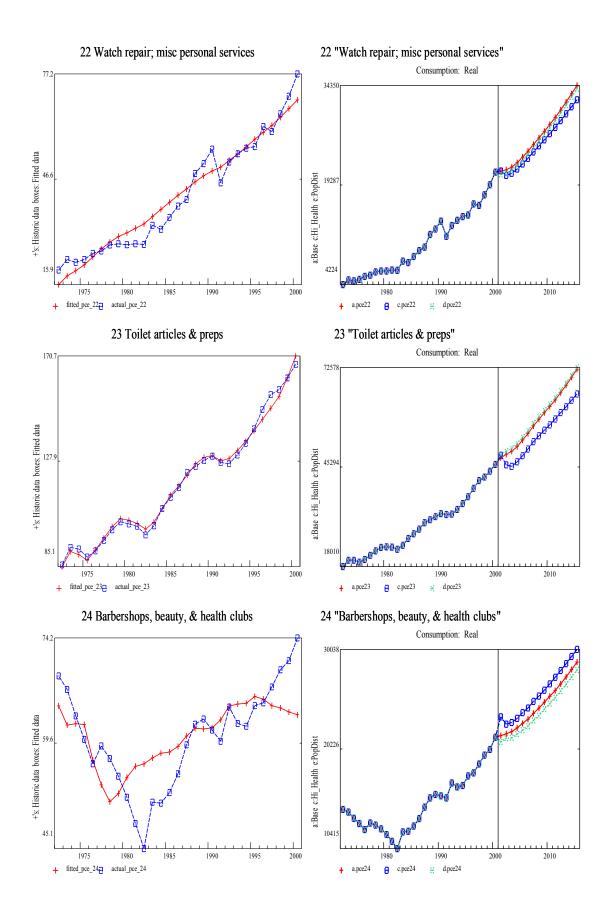


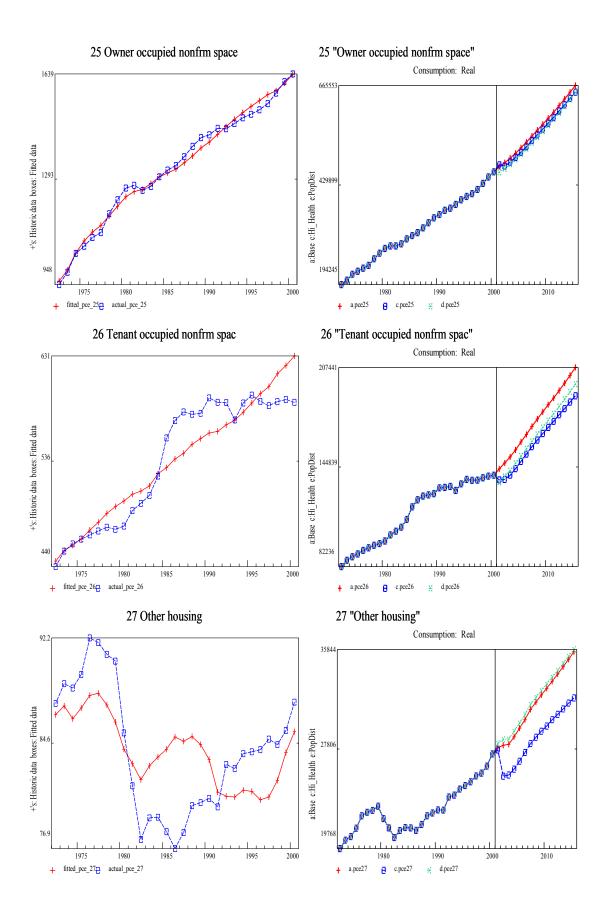


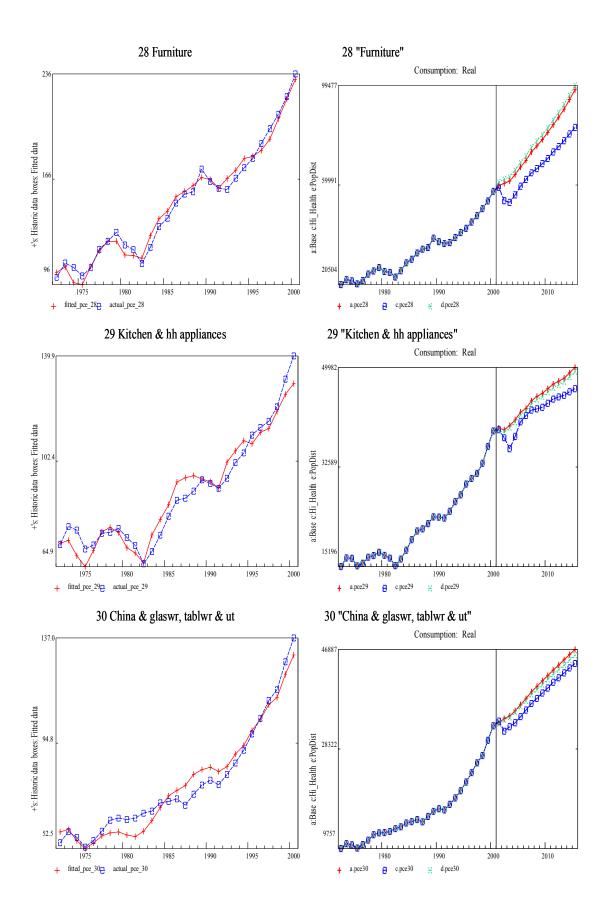


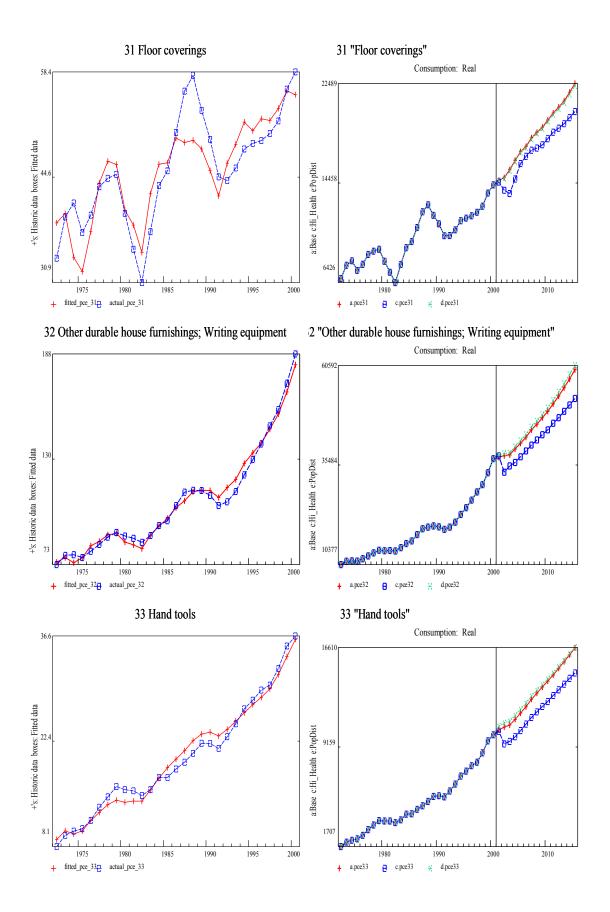


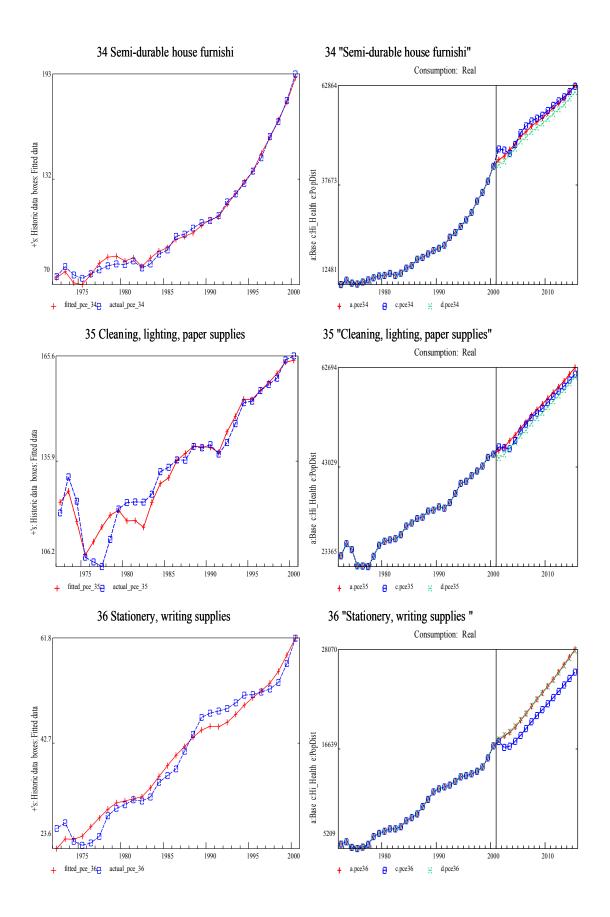


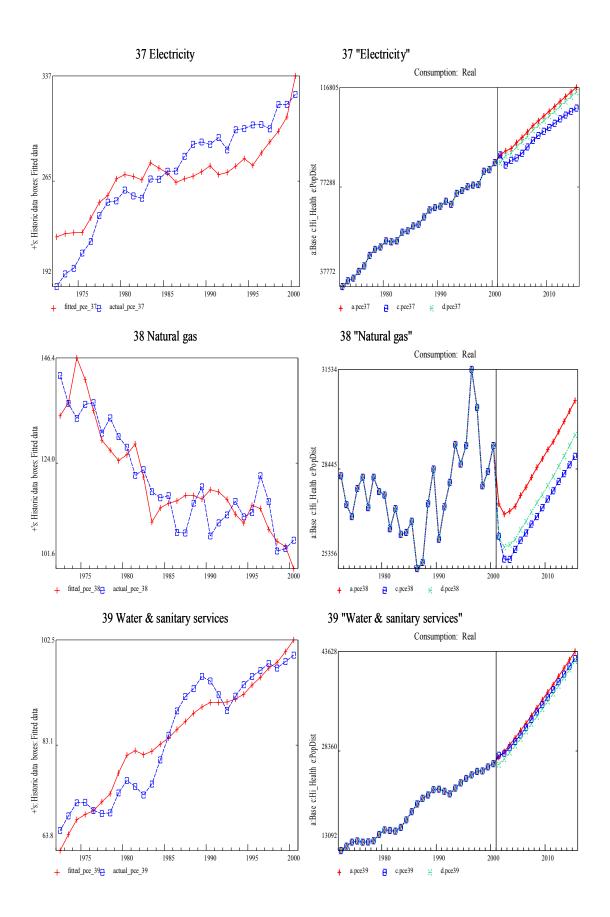


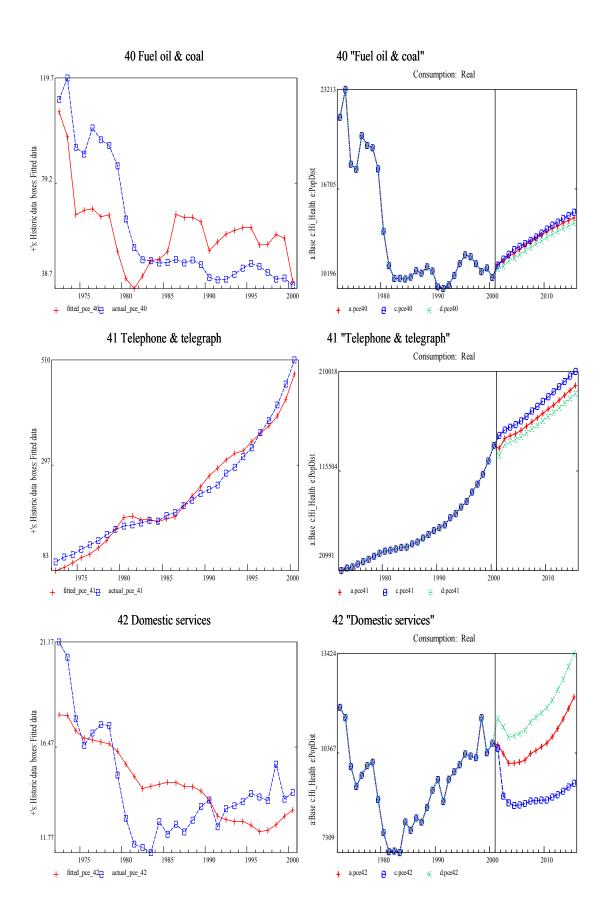


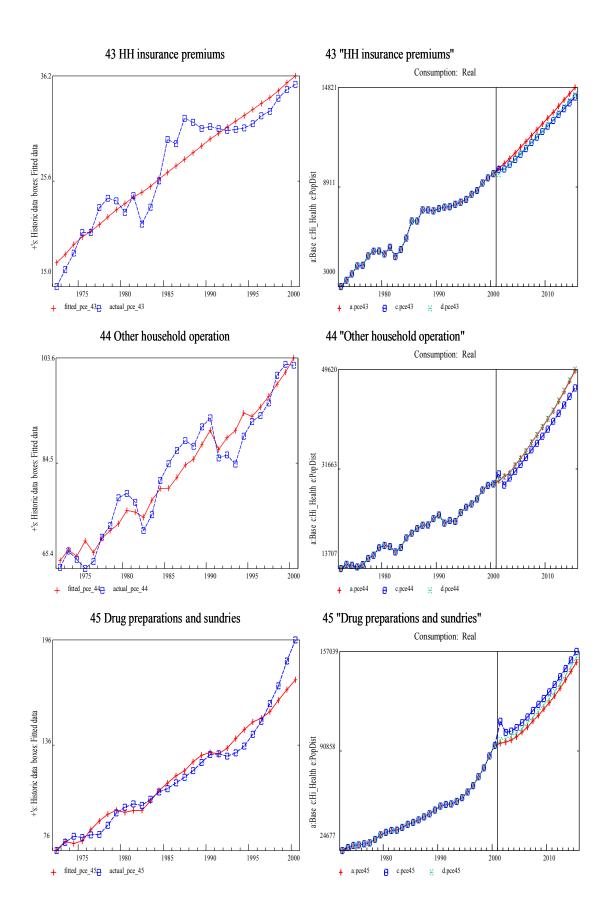


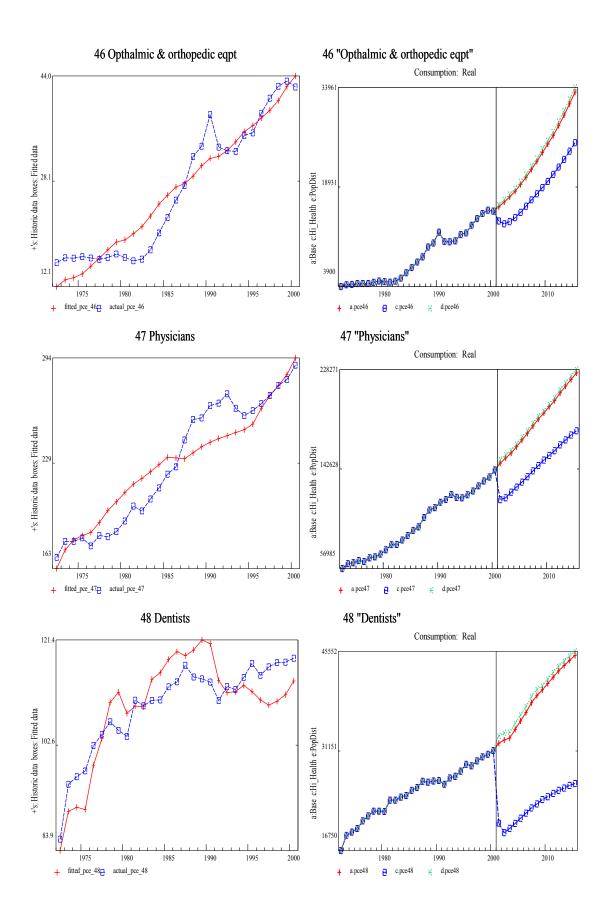


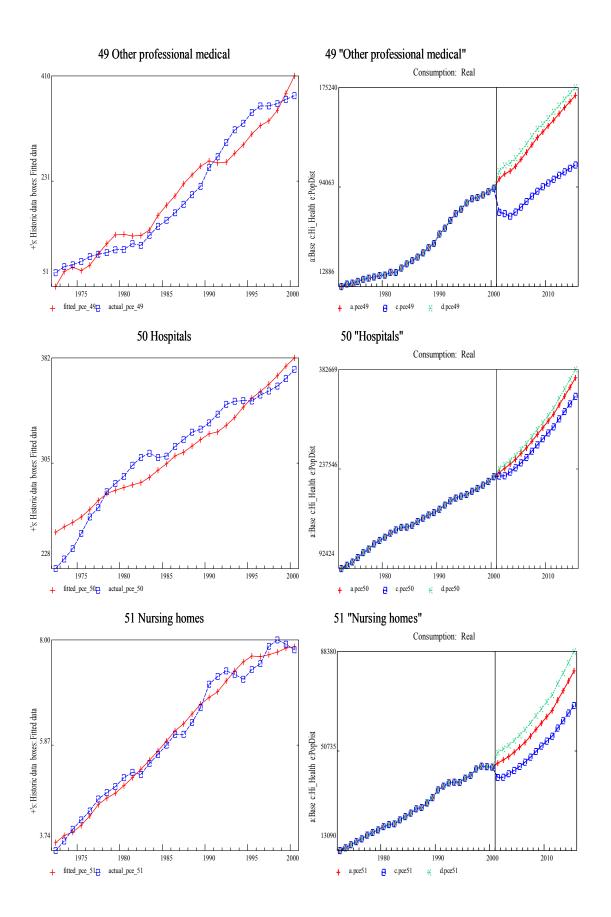


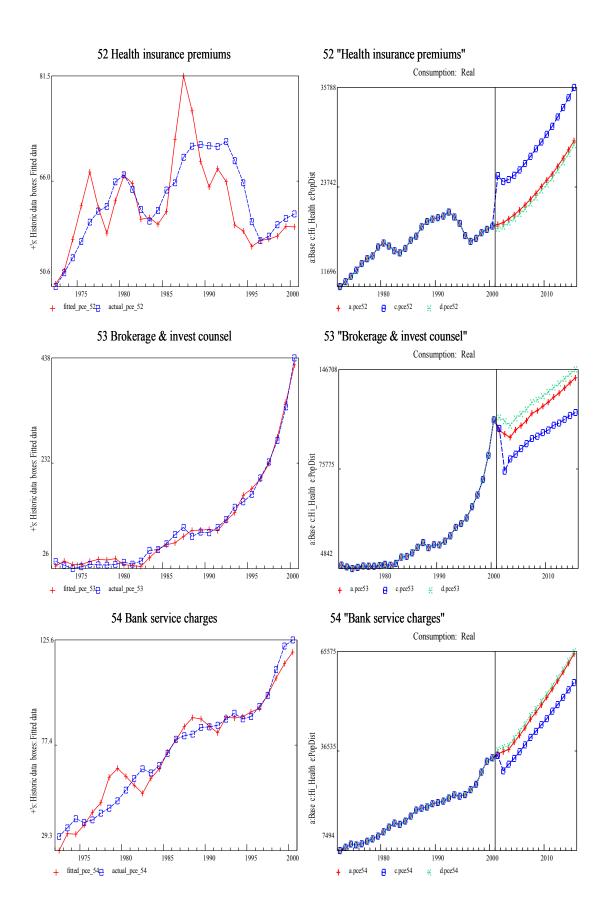


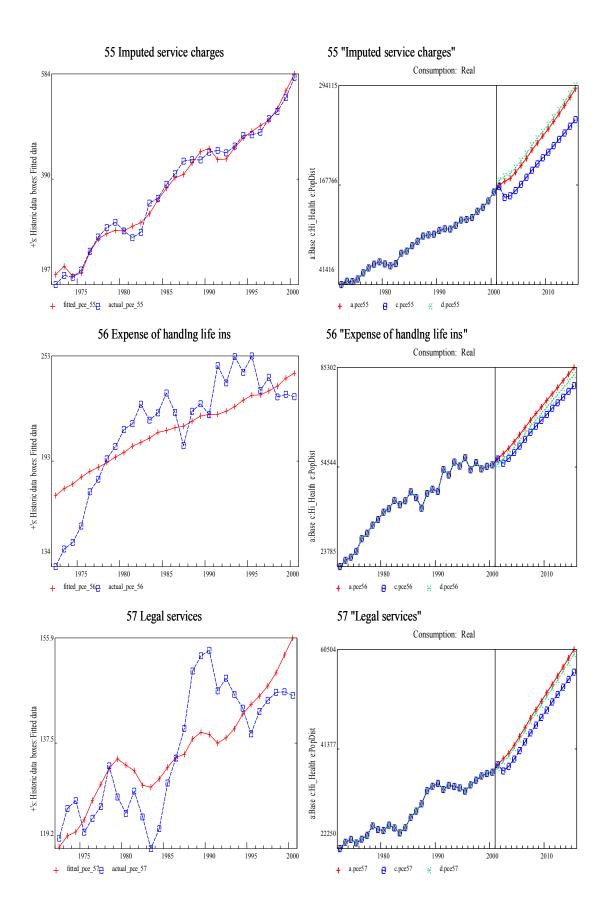


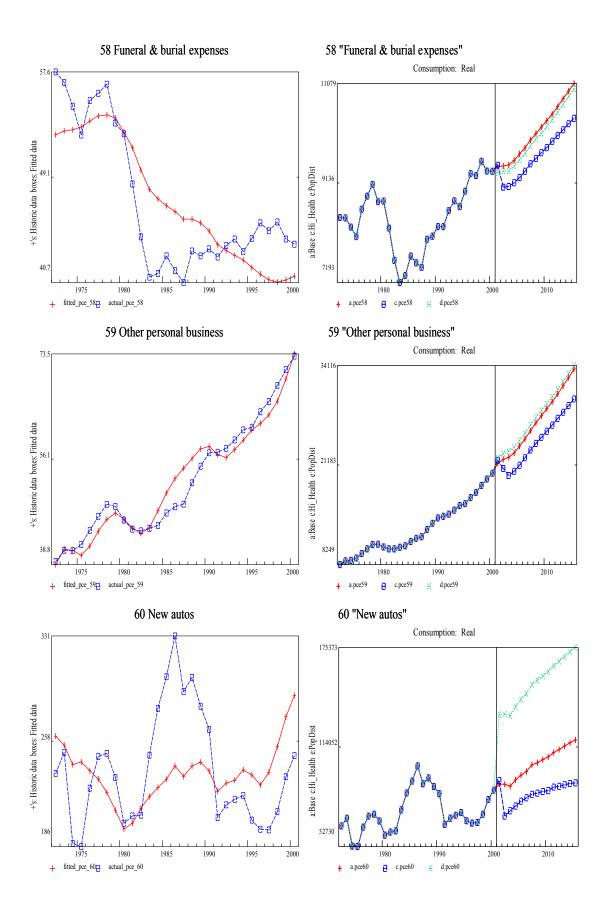


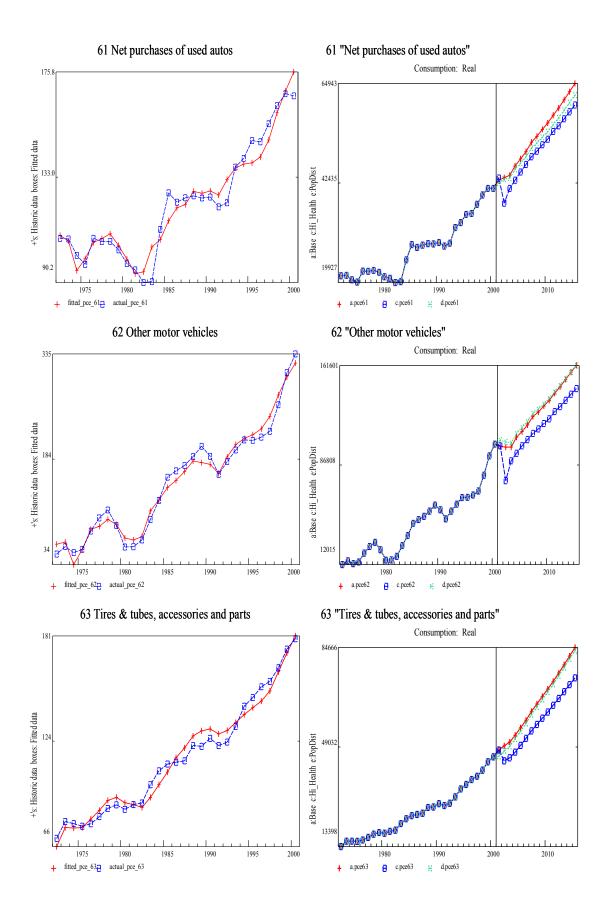


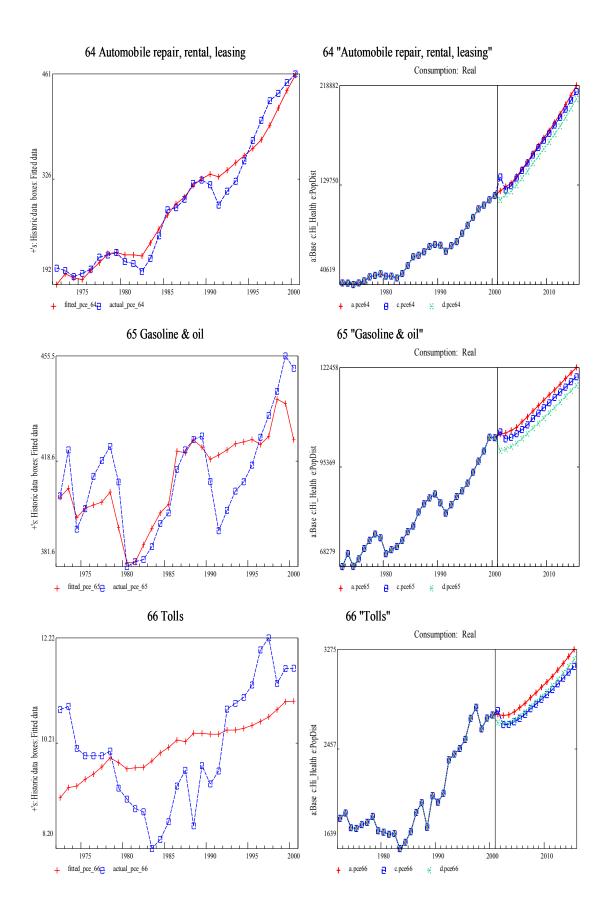


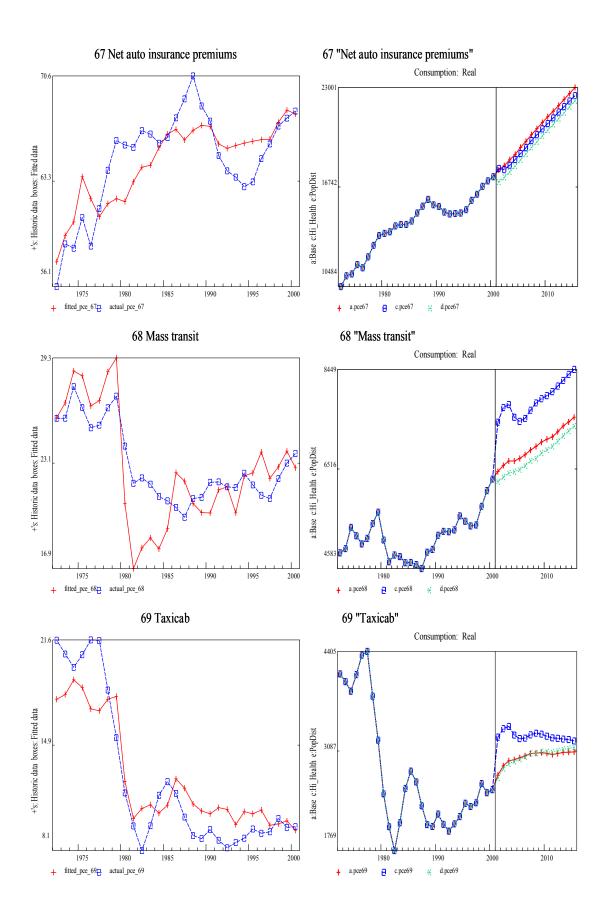


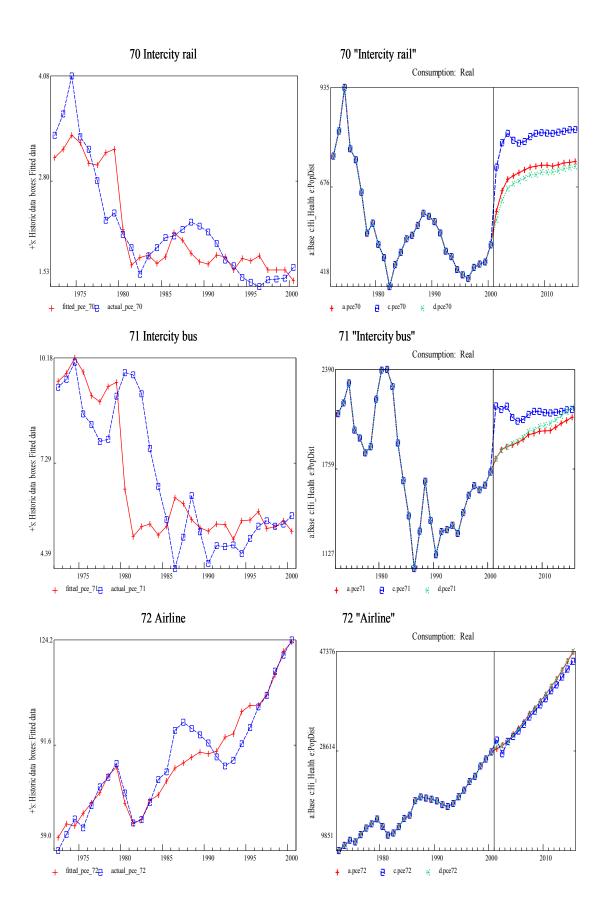


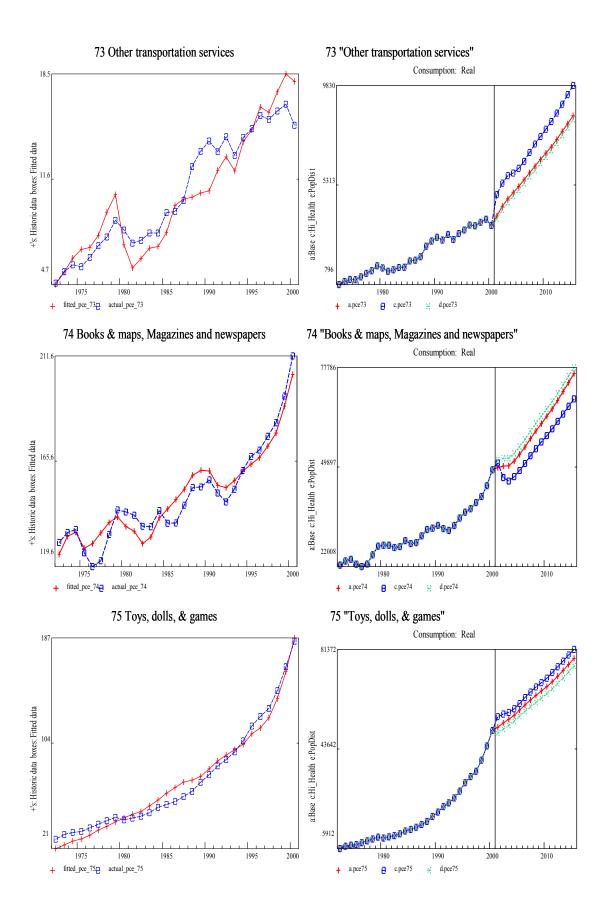


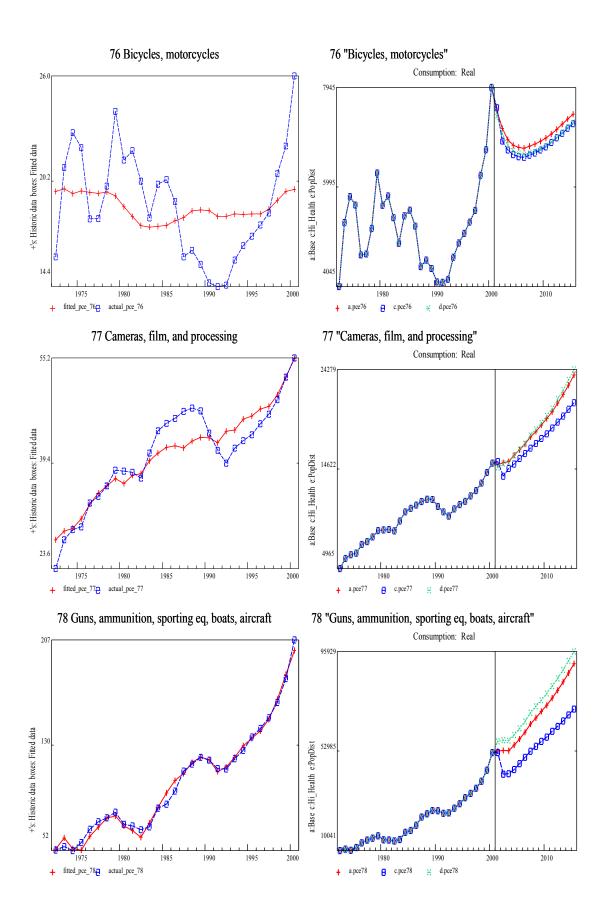


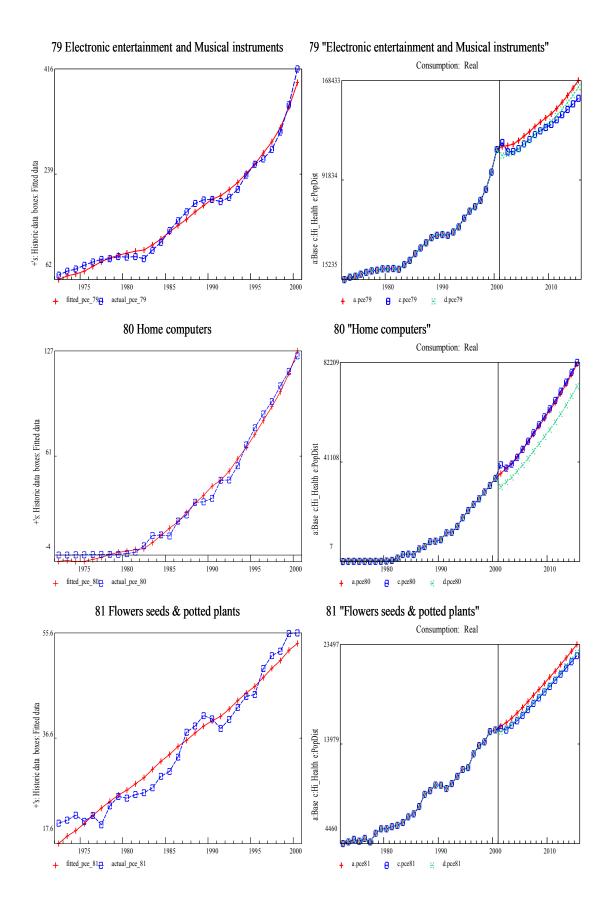


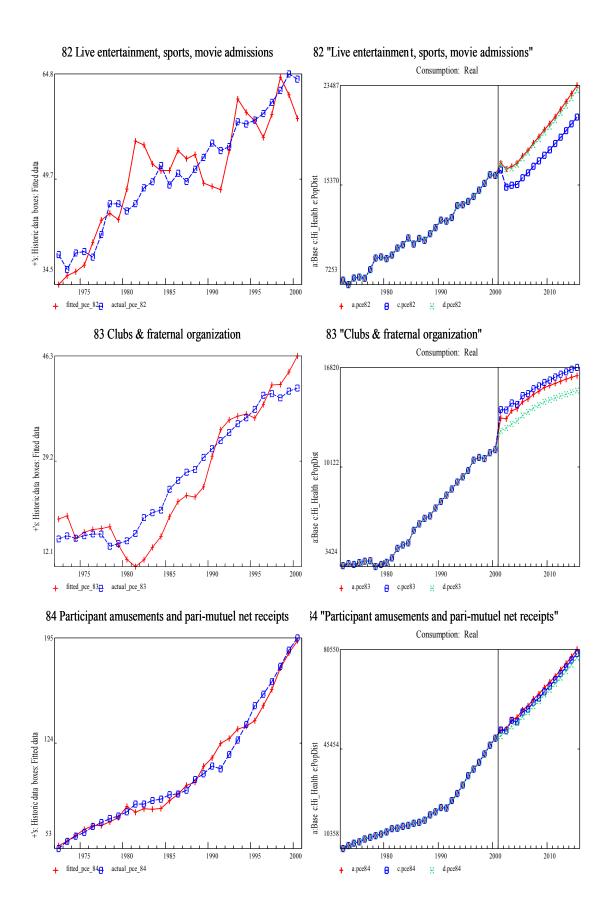


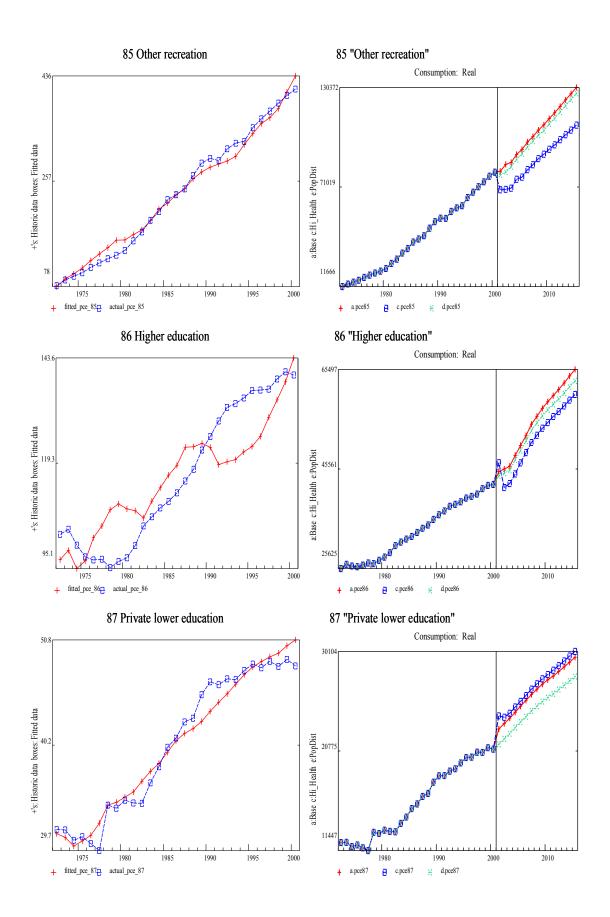


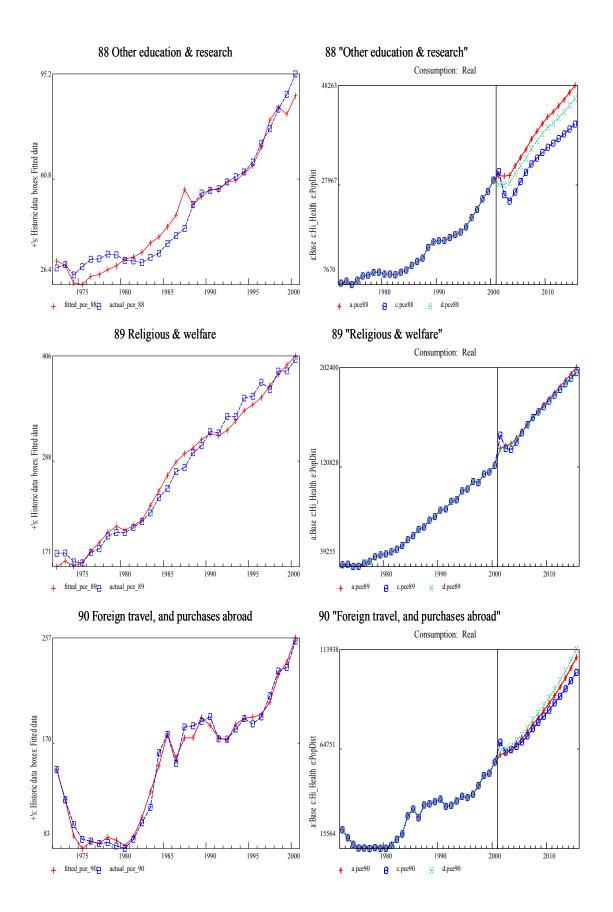


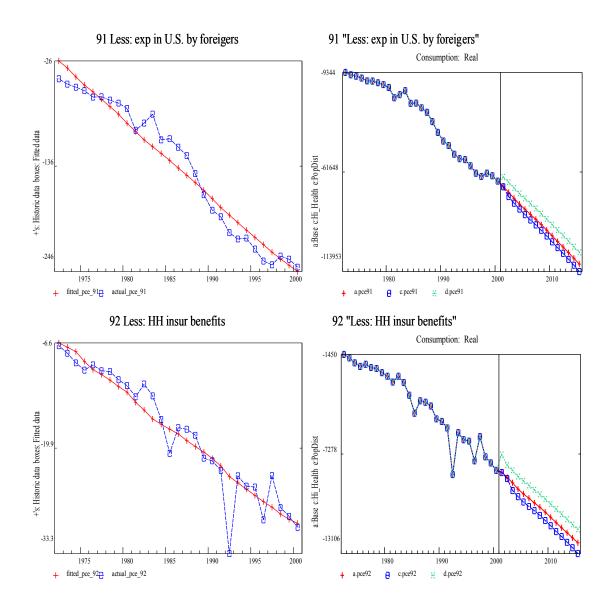












## Appendix 3

Products 3, 4, 5, 7, 8, 9, and 11-20 are normalized by respective "populs."

Term no.	<u>Independent variables</u>
1	Linear time trend
2	Treasury bill rate
3	Total transfer payments
4	Unemployment insurance
5	Benefits: hospital and medical insurance
6	Fraction of the population over age 65
7	Residential construction spending
8	Cstar 61: Net purchases of used automobiles
9	Stock of automobiles and light trucks
10	Expected gas and oil prices
11	Disposable income, 1987\$
12	Housing stock
13	Construction: Religious structures
14	Construction: Educational buildings
15	Cstar 93: Alcohol on premises
16	Cstar 94: Other jewelry and clothing services
17	Cstar 95: Hotels
18	Cstar 96: Other fuels
19	Cstar 97: Auto parts
20	Cstar 98: Electronic repair and rental

Product		
<u>number</u>	Product title	<u>Terms</u>
1	Meat	1
2	Dairy products	1
3	Poultry and eggs	1
4	Fresh fruit and vegetables	1
5	Processed fruit and vegetables	1
6	Cereal and bakery products	1
7	Fats & oils	1
8	Sugar & sweets	1
9	Nonalcoholic beverages	1
10	Other prepared food	1
11	Fish & seafood	1
12	Pet food	1
13	Alcohol for off-premise consumption	1
14	Purchased meals, food furnished employee, on farms .	1
15	Tobacco	1
16	Footwear	1
17	Clothing, Women's & girls'	1
18	Clothing, Men's & boys' and Military	1
19	Luggage	
20	Cleaning, laundering, repair of clothing and shoes .	1, 16
21	Jewelry & watches	1, 16
22	Watch repair; miscellaneous personal services	
23	Toilet articles & preparations	1
24	Barbershops, beauty, & health clubs	
25	Owner occupied nonfirm space	
26	Tenant occupied nonfirm space	
27	Other housing	1, 17
28	Furniture	
29	Kitchen & household appliances	1, 2, 7

30	China & glassware, tableware & ut	1		
31	Floor coverings	1,	7	
32	Other durable house furnishings; Writing equipment .	1		
33	Hand tools			
34	Semi-durable house furnishings		7	
35	Cleaning, lighting, paper supplies			
36	Stationery, writing supplies			
37	Electricity			
38	Natural gas		12	
39	Water & sanitary services			
40	Fuel oil & coal			
41	Telephone & telegraph		12	
41 42	Domestic services			
43	HH insurance premiums			
44	Other household operation		_	
45	Drug preparations and sundries			
46	Ophthalmic & orthopedic equipment			
47	Physicians			
48	Dentists			
49	Other professional medical			
50	Hospitals	1,	5	
51	Nursing homes			
52	Health insurance premiums	1,	5	
53	Brokerage & investment counsel	1		
54	Bank service charges	1		
55	Imputed service charges			
56	Expense of handling life insurance			
57	Legal services		6	
58	Funeral & burial expenses			
59	Other personal business			
60	New autos		2.	8.10
61	Net purchases of used autos			
62	Other motor vehicles			
63	Tires & tubes, accessories and parts			
64	Automobile repair, rental, leasing			10
65	Gasoline & oil		O	
56	Tolls			
50 67	Net auto insurance premiums			
5 <i>1</i> 58	<u>-</u>			
58 59	Mass transit			
5 5	Taxicab			
70	Intercity rail			
71	Intercity bus			
72	Airline	Ι		
73	Other transportation services			
7 4	Books & maps, magazines and newspapers			
75	Toys, dolls, & games	1		
76	Bicycles, motorcycles		6,	10
77	Cameras, film, and processing			
78	Guns, ammunition, sporting equipment, boats, aircraft			
79	Electronic entertainment and Musical instruments	1,	20	
30	Home computers		20	
31	Flowers seeds & potted plants			
32	Live entertainment, sports, movie admissions			
33	Clubs & fraternal organization			
3 4	Participant amusements and pari-mutuel net receipts .			
35	Other recreation			
36	Higher education		14	

87	Private lower education	
88	Other education & research 1	, 14
89	Religious & welfare	, 13
90	Foreign travel, and purchases abroad 1	
91	Less: expenditures in U.S. by foreigners 1	
92	Less: HH insurance benefits	