Adjusting DMSP Industry MFP to Account for Changes in the Composition of Labor

Cindy Zoghi
Research Economist
US BLS Division of Productivity Research

July, 2014

EXECUTIVE SUMMARY:

- Although there has been considerable demand for a sectoral labor composition adjustment to multifactor productivity, the BLS has not produced one until now due to concerns about insufficient data to measure hours and average wages for workers within detailed industry, age, gender and education groups.
- The American Community Survey (2000 forward) contains over 800,000 workers per year, which improves the accuracy of wage and hours estimates within groups; however, there is a long delay before the data are released—labor composition for a given year cannot be estimated until November two years later.
- The March Income Supplement to the Current Population Survey (1987 forward) is currently used to estimate labor composition for the private non-farm business sector. It contains around 63,000 workers per year, a much smaller number than the ACS. With the March CPS labor composition for a given year can be estimated in October of the following year.
- The Current Population Survey Outgoing Rotations Group (1987 forward) contains over 135,000 workers per year, and has the shortest delay before data are released--labor composition for a given year can be estimated in February of the following year.
- In addition, there are other small differences between the datasets in potential sources of error or response bias, industry classification, and identification of self-employment. These do not point clearly toward one data source as being more precise than the others.
- With the exception of the agriculture industries and the transportation industries, multifactor productivity measures for the 3-digit industries do not vary greatly with the choice of data for the labor composition adjustment—they all perform relatively well, none adding excess volatility to MFP.
- The recommendation of this paper is that a sectoral labor composition index can be reasonably estimated for most 3-digit industries using any of the three datasets; however, the CPS Outgoing Rotation Group offers the best combination of a fairly large dataset with the least release delay.
- Labor composition in the individual 3 digit agriculture and transportation industries should not be measured; rather a single labor composition index for agriculture and one for transportation should be used.

a. Introduction and Methodology

The labor composition index adjusts labor hours for changes in the demographic composition of the hours worked. Early papers making such adjustments include Denison (1962), and Jorgenson and Griliches (1967). The labor composition model, as described in BLS (1993), generalizes the production function used for multifactor productivity to allow multiple types of labor (as well as capital) to produce output. It can be written as:

(1) $$Q = A_t * f(k, h_1, \ldots h_m)$$

where output *Q* is produced by capital, *k*, by *m* different types of labor hours, h_1, …h_m, and by the technology available at time *t*, A_t. A more detailed production function would include many types of capital as well, but for simplicity, a single homogeneous capital input is used here.

Taking the natural logarithm of both sides, differentiating with respect to time, and rearranging terms, equation (1) can be expressed as a relationship between multifactor productivity and growth rates of output and inputs:

(2) $$\frac{\dot{A}}{A} = \frac{\dot{Q}}{Q} - \left(\frac{\partial f}{\partial k} * \frac{\dot{k}}{k} + \frac{\partial f}{\partial h_1} * \frac{\dot{h}_1}{h_1} + \ldots + \frac{\partial f}{\partial h_m} * \frac{\dot{h}_m}{h_m} \right)$$

where the dot notation indicates the growth rate of that variable. The growth rate of multifactor productivity is expressed as $\dot{A}/A$, which is a shorthand notation for the partial derivative of the log production function with respect to time. The terms $\partial f/\partial k$ and $\partial f/\partial h_j$ are partial derivatives of the log production function with respect to the inputs, also known as output elasticities, or the percent changes in output resulting from a one percent increase in the respective inputs. They are in practice unobservable. Under the assumptions of constant returns to scale and perfect competition in product

and input markets, each elasticity is equal to the share of total costs paid to that input. In the case of labor, that is calculated as the product of labor's share of total costs and each type of labor's share of the total wage bill.

If the underlying data source that the BLS uses to estimate multifactor productivity contained detailed demographic information that could be used to identify separate types of workers, the multifactor productivity estimation would directly measure each type of worker as a separate input to the production function. However, the Current Employment Statistics (CES), which is an establishment dataset, does not contain such information on the workers. As a result, the BLS must estimate an index of labor composition from an alternate data source and use that index to adjust the CES labor input.

Assuming that the labor input is separable from capital, an aggregate labor input equation can be derived:

(3) $$\frac{\dot{L}}{L} = s_{h_1}\frac{\dot{h}_1}{h_1} + \ldots + s_{h_m}\frac{\dot{h}_m}{h_m}$$

where s_{hi} is the share of the total wage bill that is spent on each particular type of labor. Under a translog production function, Diewert (1976) showed that changes in input are exactly measured by changes in Tornqvist indexes. Thus, although $\frac{\dot{L}}{L}$ is the instantaneous rate of change in composition-adjusted labor input, it can be replaced by annual rates of change, measured with a Tornqvist index as the difference in the natural logarithm of successive observations, with the weights equal to the mean of the factor shares in the corresponding pair of years:

(4) $$\Delta \ln L = \sum_j \frac{1}{2}(s_{h_j}(t) + s_{h_j}(t-1))\Delta \ln h_j$$

Groups that make up a very small portion of the total wage bill will not have much impact on the labor input measure.

Changes in the index of labor composition, LC, are defined as the difference between the change in composition-adjusted labor input given in (4), and the change in the sum of unweighted hours:

(5) $$\Delta \ln LC = \Delta \ln L - \Delta \ln H = \Delta \ln \frac{L}{H}$$

In practice, estimation of the labor composition index requires a count of the number of hours worked by each type of worker, as well as cost share weights for each type of worker. Cost share weights may be calculated using either actual mean observed wages, as in Denison (1974), Gollop and Jorgenson (1980), Jorgenson, Gollop and Fraumeni (1987), and Jorgenson, Ho and Stiroh (2005) or, as BLS (1993) did, replacing actual wages with imputed wages, where the imputations are obtained from a standard Mincer wage regression (see BLS, 1993, Appendix E).

Currently, the BLS uses a labor composition index to adjust the labor input in the private business, private non-farm business, and total economy multifactor productivity measures. However there has been considerable demand to produce indexes for specific detailed industries, as well as for manufacturing as a whole, similar to Gollop and Jorgenson (1980, 1983) and Jorgenson, Gollop and Fraumeni (1987). This paper assesses the feasibility of constructing separate labor composition indexes for each of the 18 3-digit NAICS manufacturing and 42 non-manufacturing industries for which the Major Sector Productivity Program (DMSP) measures multifactor productivity (MFP). Currently, DMSP makes no adjustment in these MFP measures, which thereby assumes that labor composition is constant over time; this could improve upon that assumption. The main issue is whether labor composition indexes for more detailed industries can be reliably estimated using currently-available data sources. Additionally, this paper compares the estimation of manufacturing MFP by including a

single manufacturing labor composition index to that estimated by aggregating up from the 18 manufacturing industries, each with its own labor composition index.

In the next section, we look at potential sources of data for estimating these labor composition indexes, and discuss the strengths and weaknesses of each source. We then estimate labor composition indexes separately using each of the potential data sources, and compare the results. Finally, we incorporate these labor composition indexes separately into multifactor productivity to determine how they perform.

b. Potential Data Sources

The BLS labor composition index was first estimated in 1993 (see BLS Bulletin 2426). Its estimation requires a consistent series of hours worked and average wages earned by workers of a particular demographic set. Maintaining most of the age, education and gender categories that are used for the private non-farm labor composition estimation and then further dividing workers by the industry of their job requires a very large sample of workers.

Current Population Survey—March Supplement

The Current Population Survey is a monthly survey of about 60,000 households, conducted by the Census Bureau for the Bureau of Labor Statistics to measure labor force participation and employment. The March Annual Demographic File and Income Supplement includes questions about income received and labor market activities in the previous year. The number of workers captured in the March CPS ranges from around 55,000 in the earlier years to 75,000 or more from 2002 forward (there was an expansion of the number of households sampled beginning in mid 2001)

Current Population Survey—Outgoing Rotation Group

Households in the CPS are interviewed for four consecutive months, are out of the sample for the next eight months, and are then interviewed again for four consecutive months. Respondents in months in sample (MIS) four and eight, known as “outgoing rotations” because they will not be interviewed the following month, are asked additional questions about usual weekly hours and earnings. Approximately one fourth of respondents are in the two outgoing rotations in any given month, which means that the annual ORG samples are about three times the size of the monthly samples. Thus, there are over 120,000 workers in each year of the ORG files.

American Community Survey

The American Community Survey is a household survey conducted by the Census Bureau and intended to replace the long form of the decennial Census program. The income and labor market questions are similar to those asked in the March CPS. However, one important difference is that the questions in the ACS are self-administered, which means that there is likely to be more reporting error. A recent paper by Baum-Snow and Neal (2009) shows that many ACS respondents mistakenly reported usual daily hours instead of usual weekly hours, as well as making other errors that tended to inflate wages. The Census Bureau began collecting test data in 2000, and went into full production in 2005. In the test years, the sample was approximately 400,000 workers, and after 2005 it increased to 1.1 million and up.

c. Data strengths and weaknesses

a. Coverage

As noted above, the American Community Survey is the largest of the potential data sources, with more than three times the number of workers of the next largest sample. It is also the shortest sample, however, with data only available from 2000 forward. The March CPS and CPS ORG, on the other hand, can be used to estimate a labor composition index from 1987 forward, covering the entire

period of the BLS Multifactor Productivity series. Thus, there is a tradeoff between the depth and length of the data samples. Ideally, we would like the longest possible labor composition series, to provide the most information to our users. However, we must determine the costs, in terms of precision of our estimates, of sacrificing depth for length.

Dividing the workers into seven education categories (6^{th} grade or less, 7^{th} – 8^{th}, 9^{th}-11^{th}, high school graduate, some college, Bachelor's degree, advanced degree[1]), nine age groups (15-16, 17-18, 19-21, 22-24, 25-34, 35-44, 45-54, 55-64, and 65+)[2] and two genders yields 126 cells. A few of these combinations are quite rare in all of the datasets, so we aggregate them (for example, 15-16 year old workers with advanced degrees), reducing the number of cells to 104. While the full sample is likely to have quite a few workers of each of these education × age × gender cells, once the sample is disaggregated by industry, there will be many empty cells. In part, this is a true representation of the workforce—there may not, in fact, be any 19-21 year old female Ph.D.s working in mining—on the other hand, this is also often a feature of the data sample size.

Tables 1a and 1b show the average annual number of observations in each manufacturing and nonmanufacturing industry, respectively, as well as the average percent of the 104 demographic types that are unpopulated, and the average percent that are fairly well populated (with five or more workers). Many industries are fairly well populated, with several hundred workers sampled even using the smallest sample, and with half or more of the demographic types having at least five workers sampled. Nevertheless there are quite a few industries that have a very low number of workers most years, and a large number of cells containing fewer than five workers. Among the manufacturing

[1] In 1992, the CPS changed the coding of education from a measure of the highest grade attended in years to the highest level of school or degree completed. Frazis and Stewart (1999) demonstrate the bridge from one measure to the other, which is followed here.

[2] This is slightly fewer than the eleven age groupings used in the major sector labor composition estimation.

industries, Petroleum and Coal, Wood Products and Non-Metallic Mineral Products have fewer than 30% of cells with five or more workers in the March CPS; the percentage is only slightly higher in the CPS ORG. In the ACS, however, all manufacturing industries with the exception of Petroleum and Coal Products have 60% or more cells with five or more workers. Among the non-manufacturing industries, the main concerns are with the mining and transportation industries as well as the management of companies industry. Although there are many more workers observed in the ACS in these industries than in the March CPS or CPS ORG, even in the ACS the percent of cells with five or more workers is fairly low.

The strategy going forward in this paper will be to see whether the high number of empty cells and/or low percentage of well-populated cells results in a highly volatile labor composition index for that industry, and whether incorporating a labor composition index with that volatility has an excessively large impact on multifactor productivity for that industry. We will compare these results across the datasets and determine whether the tradeoff of a longer data series (March CPS or CPS ORG) comes at too high a cost in terms of introducing excessive volatility to our MFP estimates, or whether there are other methods of smoothing out the data that can improve these results.

b. Wage measurement

In the March CPS and in the ACS, workers are asked for total wage and salary income at all jobs in the previous year. This has the advantage of covering not just a primary job and a secondary job, but all jobs, and includes bonuses, commissions, etc.; however, it has the disadvantage of being retrospective, and subject to recall bias. Since the labor composition adjustment uses hourly wages in its weights, the ACS and March CPS annual wage and salary income must be divided by an estimated number of hours worked the previous year—based on the usual hours worked per week and the number of weeks worked. This introduces another potential source of measurement error to the ACS

and March CPS wage estimates, if the sum of usual weekly hours and reported weeks worked does not equal the total number of hours upon which the annual wage and salary income is based.

In the CPS ORG, on the other hand, workers are asked for weekly and/or hourly wages in the current primary job. This is much less likely to be subject to recall bias or from the measurement error of dividing by an estimate of hours worked, but assumes that the worker's wage rate remains constant throughout the entire month, based on one week's observed wage rate. Additionally, the CPS ORG does not ask workers about the wage rate on any secondary jobs, thus any hours at that secondary job must be assigned either the worker's primary job rate of pay, or the rate of pay for a similar worker whose primary job is in the same industry as the secondary job, neither of which may be a realistic assumption[3]. So, there are tradeoffs in using any of the three datasets, in terms of their unbiasedness in measuring wages.

Regardless of which dataset we use, there are occasional wage outliers; while these are not a problem in the more aggregate private non-farm data, or even in the larger industries such as retail, they can cause quite large jumps in the labor composition index and even ultimately in the MFP index for smaller industries. First, we account for outliers by using the median wage for a demographic type as our weight, as opposed to the mean. Despite this, there remain some outliers—for example, when one type of worker in a small industry has only one or two observations. Rather than dropping the outlier (which would result in a loss of hours in the industry), we replace the outlying wage value (identified as any median hourly wage that exceeds $200[4]) with the next lowest median wage for another type of worker in that industry. This prevents single outlying wage observations from causing spikes in MFP.

[3] Here, the second job is assigned the wage rate for a similar worker (by age group, education, gender) in the same industry as the second job. A previous draft assigned to the second job the wage rate of the primary job; results were unchanged.

[4] This corresponds to an annual income that far exceeds the typical top-coded value—if such a value were reported as an annual income it would be top-coded to a lower value by CPS, which is what we are essentially doing here.

c. Hours measurement

In the March CPS and in the ACS, workers are asked to report the number of weeks they worked during the previous year and the usual weekly hours for the weeks that they worked. In this manner, total annual hours are estimated. As with the wages, this measure is likely to suffer from retrospection bias. Additionally, because the ACS is filled out by the respondent, it is more likely that respondents misunderstand the questions. For example, Baum-Snow and Neal (2009) show that some respondents mistakenly report usual daily hours rather than weekly. In the CPS ORG, all job information pertains to the currently held main job and secondary jobs. Respondents are asked about both the actual hours worked last week at both, and about the usual hours worked per week. When the worker was at work in the reference week, the actual weekly hours is used; when the worker was with a job but not at work in the reference week, the usual weekly hours is used instead. Since respondents are not asked about the number of weeks worked per year, we multiply the weekly hours by 52/12 to get an estimate of monthly hours, and then sum across the twelve months. In fact, the worker may not have worked the same number of hours the entire month, and may not have worked all weeks during the year. In all three datasets, total annual hours is an estimated number[5], rather than an exact measure.

d. Industry identification

There are a number of complications inherent in consistently identifying the industry in which workers are employed, both over time and across datasets. The March CPS and ACS record the industry of the longest job held the previous year; ideally we would like to know the industry for each job held, in order to properly attribute the hours of each job to the correct industry. The CPS ORG records the

[5] Population weights are used to obtain total estimated hours for the entire non-institutional workforce.

industry of the first and second jobs currently held, which may or may not match the industry of whichever job the worker held for the majority of the year. Thus, the distribution of hours across industries may not match precisely across datasets, in particular if there are systematic differences in the industries in which a worker works short term, temporary or secondary jobs.

In the March CPS and CPS ORG, industries are coded according to a Census Bureau system of industries. For the years 1983-1991, industry is coded under the "1980 Industry Classification," which roughly correlates to the 1972 Standard Industrial Classification scheme. For the years 1992-2002, industry is coded under the "1990 Industry Classification," which roughly correlates to the 1987 Standard Industrial Classification scheme. For the years following 2002, industry is coded under the "2002 Census Code," which closely correlates to the 2002 North American Industry Classification System. The ACS uses the 2000 Census Codes and the 2002 Census Codes for the years 2000-2002, and 2002 forward, respectively.

Since the BLS Division of Major Sector Productivity estimates MFP for particular aggregations of 2002 NAICS industries, a complete crosswalk was necessary to bridge from each Census classification scheme to these NAICS groups. In most cases, any single detailed 1980 Census industry did not have a one-to-one match in the NAICS groups. Using information on the distribution of employment into one industry classification and the other, we are able to approximately determine which NAICS groups any given worker's hours and wages should be attributed. A full concordance table is available upon request, but as an example: 1990 Census code 731—Personnel Supply Services—is distributed between DMSP industries Administrative and Support Services (86.8%),Miscellaneous Professional, Technical and Scientific Services (5.7%), Ambulatory Health Care Services (4.6%), and Performing Arts, Sports and Museums (2.9%).

e. Identification of self-employed workers

Wages are especially difficult to estimate for unincorporated self-employed workers, because reported self-employment income includes returns to capital as well as labor[6]. We therefore assign unincorporated self-employed workers the wage rate for a similar age/education/gender wage and salary worker. In the March CPS and ACS, self-employment is identified by a worker's class at the longest job last year; class is not reported for second jobs, so we cannot make a self-employment adjustment for the amount of annual wage and salary income that derives from second jobs. In the CPS ORG, any worker whose class is self-employed on the main job is excluded from the ORG questions by the CPS; additionally, we assign a non-self-employed wage to any worker whose class of worker on the secondary job is unincorporated self-employed. Note that this might result in a slightly different hours estimate for the March CPS and the CPS ORG, since the hours of self-employed workers are not excluded in the March CPS, we are merely assigning those hours a different wage rate.

f. Timing

The March CPS is generally released in around October. However, since the income and hours questions refer to the previous year, the lag is about ten months from the end of the reference period; a 2012 labor composition index can be estimated in October 2013. The CPS ORG, which we obtain from Unicon Research Corporation, is available in February of the following year. Since we use current earnings and hours in the CPS ORG, a labor composition index for 2012 can be estimated in February 2013. Data from the American Community Survey are released in November of the year following the survey; since we are again using questions on the previous year's income and hours worked, a labor composition index for 2012 cannot be estimated until November 2014.

[6] It is not uncommon for respondents to report losses.

g. Summary of Differences

Table 4 summarizes the differences between the alternative datasets. No single dataset is optimal under every criteria. Each has its own sources of potential measurement error. The American Community Survey would seem to be the best option by virtue of the number of workers recorded; however, the delay in estimating a labor composition index using the ACS and the shortness of the data series makes it much less optimal. To determine the extent of the tradeoff between data precision and speed, as well as the importance of the various measurement errors inherent in each data set, we must consider how the labor composition indexes, and ultimately multifactor productivity look using each dataset. In particular, since demographic changes in the workforce generally occur rather gradually, a labor composition index should not have tremendous year-to-year variability—this is therefore a key criterion for evaluating alternate data sources. Before we make such comparisons, however, there is another option to consider for working around the measurement error in the smaller datasets.

d. Iterative Proportional Fitting

If none of these data sources are able to produce reliable estimates of the hours and wages of workers within the narrow categories defined, an alternative is to estimate simulated data, using an iterative proportional fitting method (RAS), similar to that introduced initially in Deming and Stephan (1940), and described by Jorgenson et. al. (1987)[7]. The RAS methodology begins with a set of starting values, and a set of marginal totals. The marginal totals represent the "known" values that we believe to have sufficient data to measure accurately each year. For example, there are 126 unique types of workers (2 genders, 9 age groups and 7 education groups). We may not have enough workers in a single dataset to accurately measure the total hours in each of the 126 cells, but we will have enough data to measure the total hours for the 18 gender/age combinations, the 14 gender/education combinations, or

[7] An excellent data example of how to perform iterative proportional fitting is given in Hunsinger (2008).

the 63 age/education groups. The objective is to sequentially adjust the seed cell values repeatedly until the row, column and "slice" totals match these marginal totals.

The process of adjustment requires first proportionally adjusting each row of starting values to equal its respective gender/age marginal total, then proportionally adjusting each column of starting values to equal its respective gender/education marginal total, and finally proportionally adjusting each "slice" of starting values to equal its respective age/education marginal total. This completes the first iteration. Each adjustment somewhat undoes the previous adjustment, however, making it necessary to repeat the sequence multiple times until the changes in each round are very minimal. When the sum of all the changes between one round and the next reaches less than one percent of the total sum of hours (or wages), the iterating stops.

The iteratively fitted dataset of hours and wages by age, education and gender is created from Census seed values, fitted to March CPS marginal totals[8]. For the remainder of the paper, results using this RAS dataset are compared to those using March CPS, CPS ORG, and ACS, to determine whether the RAS dataset overcomes any of the measurement biases inherent in the other datasets, and yields more reliable series of hours and wages.

e. Hours and Wages Under Alternative Potential Data Sources

Tables 2a and 2b show the average annual unweighted[9] correlation in median wages across the potential datasets, for manufacturing and non-manufacturing industries respectively. Since the ACS data are much larger, and are thus more likely to have reliable wage median estimates for the population,

[8] A similar dataset was created using other possible sets of marginal totals, including CPS ORG totals and multi-year March CPS aggregated totals. Results were no better or worse using any of these.
[9] Note that weighted correlations would be much higher, since they give greater weight to the highly populated cells, where the median wages estimates are less likely to be affected by small sample size.

wage correlations between the March (ORG) and the ACS can be considered a measure of the extent to which the smaller sample sizes in the March (ORG) will affect the labor composition index. In the manufacturing industries, most of the correlations between datasets are fairly high. Between the March, ORG and ACS, all are above 0.50; a few correlations are lower between RAS and any other dataset. The ORG and ACS are most highly correlated, followed by the March and RAS, and the March and ACS. The highest correlations are for machinery, computer and electronic equipment, transportation equipment and food, beverage and tobacco. The lowest are in paper products, petroleum and coal products, primary metals and nonmetallic minerals. In the nonmanufacturing industries, there are a few industries that have distinctly lower correlations—these are farming, forestry and fishing, management of companies and nearly all the transportation industries. Given the small number of workers in the transportation industries in Table 1b, it is not surprising that the wage correlations are low. This may indicate that a reliable labor composition index cannot be derived for these industries separately, but that some of them may need to be combined.

Tables 3a and 3b show the average annual correlation in total hours across the datasets. The correlations in hours are much higher than those for wages—around 0.90. This is not all that surprising since hours are concentrated around particular rounded numbers, such as 2080 (52 weeks*40 hours per week). Nevertheless, there are similar patterns in the correlations to those for wages—the transportation industries, and the management industry have much lower correlations in hours; additionally, information services and some of the mining industries are not as high as most other industries. Again, smaller sample sizes for these industries diminish our ability to measure hours worked precisely.

f. Labor Composition Indexes Under Alternative Potential Data Sources

The next step is to see how they perform in the labor composition index. Tables 5a and 5b show the average annual percent growth in labor composition for the manufacturing and non-manufacturing industries, respectively, for the periods 1987-1995, 1995-2000, and 2000-2009. For manufacturing, the results for March and RAS are quite similar in each time period, and the correlation in results for ORG and March, and for ORG and ACS are over 50%, which implies using different datasets does not yield utterly different results. In manufacturing, the fastest labor composition growth between 1987 and 1995 occurred in Food, Beverages and Tobacco, Plastics and Rubber Products, and Apparel and Leather. Between 1995 and 2000, the fastest growth was in Primary Metals and Fabricated Metal Products. In the most recent period, labor composition grew the fastest in Textile and Textile Mill Products, Apparel and Leather, and Miscellaneous Manufacturing.

In the non-manufacturing industries, there is some extensive volatility in the transportation industries, especially Pipeline Transportation, and in Forestry and Fishing. Excluding these industries, the results for March and RAS are very similar, and the results for March and ORG and for ORG and ACS are fairly similar, with correlations in results higher than 50%. Between 1987 and 1995, the fastest labor composition growth was in Performing Arts, Publishing, and Information. For 1995-2000, the fastest growth was in Wholesale, and Publishing. In the most recent years, labor composition grew the fastest in Publishing, Motion Pictures, Banking, Securities and Commodity Investments and Funds, Trusts and Other Financial Instruments.

Although these results indicate substantial variation across datasets in their estimated labor composition indexes, it can still be useful to incorporate labor composition into a multifactor productivity estimate. It may be that labor composition is especially volatile (or imprecisely measured) in those industries where the role of labor is less significant, or those where the MFP measure itself is fairly volatile, so that labor composition does not adversely affect the MFP measure. At the same time, there

may be other industries where the labor composition index is better measured and also plays an important role in explaining a share of the MFP growth in that industry. Rather than excluding labor composition from all MFP measures, we need to determine whether including even a volatile labor composition has an extreme impact on MFP in any industries, and if so, whether some more aggregated labor composition index might be used in place of such a narrowly defined one. To determine this, we need to estimate MFP under each assumed labor composition index, including under the assumption of no changes in the composition of labor, as we currently estimate.

g. MFP Under Alternative Labor Composition Indexes

The end goal of this exercise is to determine whether a labor composition index can be incorporated into the industry MFP calculations without adding excessive additional volatility, and if so, which source of data yields the most useful labor composition index with which to do so. Figures 1a and 1b show manufacturing and non-manufacturing MFP from 1987 through 2009, both as currently estimated (assuming no change in the composition of labor), and with the labor input adjusted by each of the potential labor composition indexes. For the most part, allowing the composition of labor to change over time does not eliminate any of the trends or patterns that appear in MFP in any industry. However, with a labor composition adjustment, many of the peaks and troughs in productivity growth are larger. The graphs indicate that the RAS estimation of labor composition occasionally yields tremendous volatility that can affect our productivity calculation in a dramatic way. On average, the effects are slightly larger when labor composition is estimated using the March CPS than the CPS ORG or the ACS. Since we do not have an a priori expectation of the contribution of changes in labor composition to productivity growth, it cannot be said for certain whether the March CPS is in fact capturing the importance of worker demographics more so than the other datasets, or whether it has greater

measurement error than the other datasets; although the relative sizes of the datasets would suggest the latter.

In a few specific industries, productivity growth measured with a labor composition adjustment does not closely follow the productivity growth with the assumption of no change in labor composition: in particular, Forestry, Fishing and Related, Transit and Ground Passenger Transportation, Pipeline Transportation, Warehousing and Storage, Legal Services, and Management of Enterprises. The transportation industries are not surprising, given the sample sizes and the volatility of labor composition growth in these industries. In the next section we will offer an improvement that will address the issues in these industries.

In some of the industries it is difficult to determine the effect of labor composition growth on productivity because the scale of the graphs is affected by one or two very large peaks or troughs in the productivity indexes, compressing the other years so that it is hard to observe how closely the labor composition adjusted numbers match. Tables 6a and 6b provide additional details on the comparison between MFP with and without a labor composition adjustment. These tables report average deviations in MFP growth from the currently calculated numbers, over the periods 1987-1995, 1995-2000 and 2000-2009. In general, these are mostly small negative numbers, showing (rightly) that MFP is slightly overestimated if labor composition is held constant, as the current calculations do. Labor composition growth affects the manufacturing industries slightly more than the non-manufacturing ones. The effects are smallest during the 1995-2000 period in all datasets, and largest from 1987-1995, although this period is only measured for the March CPS and RAS datasets. The only period for which all datasets can be compared is 2000-2009. During this time period, the effects are largest for the March CPS. The correlation in MFP measures between the current calculation and the one adjusting labor composition using the March CPS is .95 for all industries overall; for the CPS ORG adjustment it is .98; for the ACS

adjustment it is .99; and for the RAS it is only .77. With the exception of the RAS, which as was noted above leads to occasional spurious large outliers in MFP, all the datasets perform fairly well, yielding MFP indexes that are reasonably close to the current calculations.

h. Aggregating Transportation Industries and Farms, Forestry, Fishing and Related

One way to improve on the results above would be to estimate labor composition indexes at a slightly more aggregated level of detail, and then apply this aggregated index to each individual industry within the aggregate. While this results in a loss of some differences in labor composition growth between industries, in the case of industries for which the data are very sparse, it may be worth sacrificing a bit of detail for a less volatile index. In particular, the transportation industries might be aggregated from eight separate indexes to a single transportation labor composition index; additionally, Farms might be aggregated with Forestry, Fishing and Related to create a joint index.

Figure 1c shows the measured MFP for these industries using the aggregated labor composition indexes and Table 7 shows the deviations in MFP calculation from the current assumption of no labor composition growth, using these aggregated labor composition indexes. There are big improvements, particularly in the CPS March and the RAS versions. The correlations between current MFP growth and composition-adjusted MFP improve to .96 for the March CPS and .87 for the RAS.

i. Aggregation to the total Manufacturing Sector

The multifactor productivity index reported by DMSP for the total manufacturing sector is derived from a two-step Tornqvist-aggregation, aggregating up from the 18 approximately three-digit NAICS industries to a durable and a nondurable manufacturing index, and then Tornqvist aggregating a second time from durable and nondurable manufacturing to total manufacturing. Currently, the manufacturing sector assumes no growth in labor composition over time. An adjustment for the growth in labor composition could be made at various levels of detail, using either separate labor composition

indexes for each three-digit industry, one index for durable and another for nondurable, or one for the whole manufacturing sector. Figure 2 compares the difference between these three approaches. The assumption of zero growth in labor composition yields higher MFP indexes than with any of the three labor composition adjustments. Beyond that, none of the three possible adjustments causes MFP to differ significantly. Since the "adding up" property is somewhat desirable all else equal, this paper recommends applying separate industry labor composition indexes and Tornqvist aggregating to the total manufacturing level.

j. Conclusion and Recommendations.

There has been substantial demand for the BLS to develop a labor composition adjustment to labor input at the same level of industry detail for which DMSP currently produces MFP indexes. This paper explores potential datasets and methods that might be used to develop such measures, and assesses the feasibility of doing so. While we recognize that changes in the demographics of workers yield important differences in the marginal productivity of an hour of labor, it is important to tread with caution before introducing an adjustment to labor input that might add spurious volatility to the series.

After compressing the number of demographic characteristics a bit, "top-coding" outlying wage medians, and finally aggregating a few particularly unpopulated industries, we arrived at three measures of labor composition that yielded essentially the same patterns and trends in productivity growth as the unadjusted measures. This is realistic, since we would not expect labor composition to have a particularly large effect in either direction on MFP. The RAS methodology does not appear to be a candidate for labor composition estimation, since it produces occasional dramatic outliers. Between the remaining three datasets, the ACS produces results that most closely parallel the unadjusted numbers, followed by the CPS ORG. However, MFP calculated under any of the three demonstrates a high correlation with an MFP that assumes no growth in the composition of labor. Given that the various

measurement errors of the alternative datasets do not appear to dramatically affect the final MFP indexes, the deciding factors, then, must be the length of the data series and the speed with which the labor composition indexes can be produced. As such, the CPS ORG appears to be the best data source for going forward with the series. It extends back to the beginning of the multifactor productivity series, 1987, and labor composition indexes can be produced as early as February of the following year. Most importantly, it is definitely feasible to incorporate a labor composition adjustment to MFP for the 18 manufacturing and 42 non-manufacturing industries for which DMSP currently calculates MFP, and to incorporate those adjustments into a total manufacturing sector MFP index.

Table 1a. Average Annual Data Coverage by Industry in March CPS, CPS ORG and ACS--Manufacturing

	Avg. # Observations			Avg. % Empty Cells			Avg. % Cells with 5+		
	Mar	*ORG*	*ACS*	*Mar*	*ORG*	*ACS*	*Mar*	*ORG*	*ACS*
Non-Durable	4379	8563	44476	3.2	2.7	0.1	87.7	90	96.4
Food, Beverage, Tobacco	1276	2458	13208	9.0	6.7	1.4	67.5	77	91.8
Textile, Textile Products	366	643	2978	18.9	16.8	8.8	55.7	61	70.5
Apparel, Leather	545	819	2720	16.9	15.0	7.7	52.8	60	74.1
Paper Products	351	725	3914	25.0	21.2	12.1	48.3	54	63.0
Printing, Related Support	484	1015	5307	26.3	22.4	7.7	34.8	47	73.8
Petroleum, Coal	100	220	1528	57.2	48.9	32.7	12.3	21	40.1
Chemical Products	803	1710	9823	21.8	17.1	5.7	46.8	56	76.1
Plastics, Rubber Products	453	973	4999	23.7	18.9	8.4	41.9	52	72.1
Durable	6501	13781	79794	3.8	2.4	0.2	88.9	92	97.6
Wood Products	320	683	4125	42.8	29.4	9.3	21.6	34	67.8
Nonmetallic Mineral Products	335	687	3916	42.7	33.3	11.9	20.4	32	64.7
Primary Metals	365	766	4650	28.7	24.5	14.3	42.1	50	62.4
Fabricated Metal Products	867	1874	10177	13.2	11.2	5.3	64.6	69	81.0
Machinery	743	1655	10487	15.2	12.6	6.3	62.5	67	76.7
Computers, Electronic Products	1134	2306	11575	16.1	13.0	5.2	62.1	68	78.8
Elect. Equip, Appliances, Etc.	389	777	3870	19.7	17.8	12.7	56.5	60	65.6
Transportation Equipment	1384	2950	18048	13.1	10.6	4.6	66.8	71	83.7
Furniture, Related Products	401	820	4137	18.4	15.6	6.5	56.5	61	72.3
Miscellaneous Manufacturing	563	1261	8808	12.4	10.6	3.8	64.4	70	84.2

Table 1b. Avg. Annual Data Coverage by Industry in March CPS, CPS ORG and ACS, Non-Manufacturing

	Avg. # Observations			Avg. % Empty Cells			Avg. % Cells with 5+		
	Mar	*ORG*	*ACS*	*Mar*	*ORG*	*ACS*	*Mar*	*ORG*	*ACS*
Farms	836	1277	8573	13.7	10.5	1.5	53.7	62	91.9
Forestry, Fishing, Related	194	296	1875	25.0	22.9	9.7	35.5	39	65.3
Oil, Gas Extraction	65	139	695	60.0	51.5	38.8	11.5	19	32.5
Mining, exc. Oil, Gas	225	468	2060	44.3	38.6	29.6	21.6	30	42.7
Support Activities for Mining	205	434	2587	46.6	39.4	22.2	21.4	30	52.8
Utilities	587	1293	7139	44.4	37.9	14.7	27.0	36	58.6
Construction	4355	9070	56230	8.6	6.9	1.3	75.4	81	91.4
Wholesale	2371	5277	32421	9.5	6.6	0.5	63.5	73	94.3
Retail	9276	19616	121604	1.8	0.4	0.0	86.0	92	100.0
Air Transportation	291	686	4294	48.8	40.5	20.6	23.4	32	48.9
Rail Transportation	168	364	1897	69.0	59.5	37.0	9.7	15	35.9
Water Transportation	45	91	530	66.6	57.9	37.2	3.9	10	28.3
Truck Transportation	861	1967	11351	33.5	26.4	8.8	35.1	47	71.6
Transit, Ground Passenger Trans.	260	609	3232	29.9	23.3	15.7	35.1	47	58.4
Pipeline Transportation	18	39	352	88.7	82.4	52.8	0.2	2	18.4
Other Transport and Support	591	1336	8506	17.9	14.1	6.5	55.2	62	75.2
Warehousing and Storage	121	256	2526	57.3	46.0	13.8	6.9	17	59.9
Publishing Industries	555	1203	6215	17.8	15.9	6.2	52.8	62	71.9
Motion Picture, Sound Recording	146	312	2581	24.6	23.7	15.2	44.4	52	56.1
Broadcasting, Telecom.	1013	2326	13210	38.7	30.1	8.8	37.3	44	69.5
Information, Data Processing Svc.	121	324	1758	32.5	28.8	26.4	35.6	44	49.4
Banking, Credit Intermediation	1851	4219	24956	24.2	19.0	5.1	48.7	56	77.4
Securities, Commodities, Invest.	393	966	6815	37.9	34.7	20.4	37.9	45	55.5
Insurance and Related Activities	1315	3031	17757	36.5	31.9	9.8	39.1	47	66.7
Funds, Trusts, Other Financial	46	113	757	50.0	44.8	20.4	25.4	38	55.5
Real Estate	875	1955	12053	17.4	13.8	3.7	50.3	64	85.9
Rental and Leasing Services	245	612	3455	19.0	16.4	8.8	53.7	60	67.8
Legal Services	661	1595	9659	24.6	22.5	15.1	48.0	56	62.7
Misc. Prof, Tech, Scientific Svcs.	1958	4713	33471	9.3	9.0	2.1	70.6	75	87.3
Computer Syst. Design, Related	579	1511	10233	48.4	39.1	17.4	28.8	39	56.3
Management of Companies	36	92	940	60.1	55.3	42.8	16.2	24	33.8
Administrative, Support Services	2531	5296	31483	2.7	1.5	0.2	86.5	91	97.2
Waste Mgmt., Remediation	181	407	2336	23.8	22.7	16.8	53.4	56	53.7
Education Services	1811	4161	32972	10.8	8.7	1.5	64.8	73	89.8
Ambulatory Health Care Services	2437	6018	39504	13.4	11.3	2.9	63.3	70	87.2
Hospitals, Nursing Care Facilities	4139	9755	60050	10.2	7.3	0.7	65.7	76	93.8
Social Assistance	1128	2554	17065	13.9	10.2	1.5	54.9	66	89.4
Perform. Arts, Sports, Museums	288	631	4238	11.6	13.2	6.5	70.4	73	71.8
Amusements, Gambling, Rec.	853	1739	14129	16.9	10.5	0.5	48.6	65	91.3
Accommodation	1153	2296	11771	11.9	7.5	1.2	55.9	70	93.0
Food Services, Drinking Places	4821	9387	59214	2.8	0.9	0.2	84.3	91	99.2
Miscellaneous Services	2813	6123	37816	3.1	2.0	0.3	84.5	88	97.7

Table 2a. Average Annual Correlations across Datasets in Median Wages by Detailed Industry, Mfg.

	Mar/ORG	*Mar/ACS*	*Mar/RAS*	*ORG/ACS*	*ORG/RAS*	*ACS/RAS*
Non-Durable	0.819	0.840	0.842	0.915	0.804	0.830
Food, Beverage, Tobacco	0.741	0.771	0.786	0.791	0.657	0.707
Textile, Textile Products	0.674	0.605	0.625	0.730	0.574	0.542
Apparel, Leather	0.686	0.621	0.613	0.664	0.510	0.528
Paper Products	0.516	0.529	0.726	0.640	0.427	0.457
Printing, Related Support	0.634	0.700	0.697	0.706	0.515	0.556
Petroleum, Coal	0.545	0.550	0.682	0.679	0.476	0.469
Chemical Products	0.505	0.599	0.830	0.659	0.459	0.534
Plastics, Rubber Products	0.792	0.807	0.833	0.854	0.711	0.737
Durable	0.828	0.820	0.841	0.926	0.821	0.860
Wood Products	0.655	0.677	0.781	0.669	0.596	0.671
Nonmetallic Mineral Products	0.560	0.577	0.771	0.601	0.524	0.557
Primary Metals	0.644	0.544	0.709	0.703	0.502	0.523
Fabricated Metal Products	0.734	0.628	0.684	0.766	0.601	0.576
Machinery	0.741	0.761	0.651	0.865	0.662	0.686
Computers, Electronic Products	0.803	0.791	0.764	0.866	0.750	0.781
Elect. Equip, Appliances, Etc.	0.763	0.725	0.762	0.756	0.646	0.690
Transportation Equipment	0.797	0.776	0.806	0.862	0.721	0.766
Furniture, Related Products	0.694	0.563	0.571	0.705	0.416	0.490
Miscellaneous Manufacturing	0.765	0.735	0.660	0.847	0.641	0.676

Table 2b. Average Annual Correlations across Datasets in Wage Medians by Worker Type, Non-mfg.

	Mar/ORG	*Mar/ACS*	*Mar/RAS*	*ORG/ACS*	*ORG/RAS*	*ACS/RAS*
Farms	0.330	0.416	0.117	0.488	-0.062	0.025
Forestry, Fishing, Related	0.213	0.225	0.237	0.517	0.154	0.130
Oil, Gas Extraction	0.483	0.591	0.816	0.632	0.472	0.556
Mining, exc. Oil, Gas	0.532	0.551	0.648	0.519	0.395	0.420
Support Activities for Mining	0.511	0.580	0.726	0.612	0.445	0.517
Utilities	0.550	0.611	0.823	0.777	0.587	0.656
Construction	0.686	0.717	0.539	0.749	0.458	0.469
Wholesale	0.669	0.696	0.732	0.855	0.669	0.727
Retail	0.758	0.868	0.736	0.923	0.765	0.830
Air Transportation	0.593	0.636	0.798	0.589	0.468	0.645
Rail Transportation	0.516	0.405	0.841	0.509	0.421	0.383
Water Transportation	0.372	0.443	0.756	0.429	0.240	0.361
Truck Transportation	0.346	0.343	0.652	0.461	0.216	0.352
Transit, Ground Passenger Transp.	0.363	0.289	0.442	0.284	0.198	0.282
Pipeline Transportation	0.478	0.041	0.949	0.300	0.457	0.198
Other Transport and Support	0.635	0.584	0.631	0.657	0.450	0.504
Warehousing and Storage	0.402	0.490	0.768	0.590	0.338	0.410
Publishing Industries	0.650	0.628	0.703	0.798	0.625	0.630
Motion Picture, Sound Recording	0.573	0.558	0.435	0.626	0.347	0.483
Broadcasting, Telecommunications	0.600	0.719	0.742	0.757	0.473	0.594
Information, Data Processing Svc.	0.598	0.624	0.621	0.702	0.458	0.524
Banking, Credit Intermediation	0.634	0.576	0.759	0.822	0.688	0.667
Securities, Commodities, Invest.	0.625	0.634	0.650	0.776	0.521	0.500
Insurance and Related Activities	0.693	0.620	0.689	0.731	0.601	0.628
Funds, Trusts, Other Financial	0.562	0.647	0.709	0.760	0.427	0.505
Real Estate	0.584	0.602	0.565	0.728	0.402	0.516
Rental and Leasing Services	0.636	0.675	0.683	0.681	0.504	0.598
Legal Services	0.712	0.683	0.470	0.736	0.411	0.504
Misc. Prof, Tech, Scientific Services	0.781	0.774	0.643	0.892	0.622	0.570
Computer Systems Design, Related	0.651	0.652	0.798	0.785	0.588	0.570
Management of Companies	0.455	0.596	0.787	0.672	0.350	0.511
Administrative, Support Services	0.789	0.719	0.624	0.801	0.558	0.721
Waste Management, Remediation	0.550	0.428	0.553	0.564	0.387	0.411
Education Services	0.749	0.720	0.744	0.825	0.721	0.687
Ambulatory Health Care Services	0.793	0.845	0.564	0.901	0.671	0.661
Hospitals, Nursing Care Facilities	0.819	0.899	0.886	0.929	0.842	0.903
Social Assistance	0.619	0.656	0.710	0.730	0.570	0.572

Performing Arts, Sports, Museums	0.567	0.484	0.277	0.420	0.192	0.167
Amusements, Gambling, Rec.	0.551	0.496	0.575	0.685	0.435	0.497
Accommodation	0.484	0.566	0.649	0.701	0.446	0.559
Food Services, Drinking Places	0.633	0.628	0.528	0.736	0.388	0.464
Miscellaneous Services	0.756	0.810	0.722	0.861	0.664	0.722

Table 3a. Average Annual Correlations across Datasets in Total Hours by Worker Type, Mfg.

	Mar/ORG	*Mar/ACS*	*Mar/RAS*	*ORG/ACS*	*ORG/RAS*	*ACS/RAS*
Non-Durable	0.989	0.988	0.998	0.992	0.991	0.990
Food, Beverage, Tobacco	0.966	0.962	0.994	0.979	0.970	0.970
Textile, Textile Products	0.868	0.856	0.981	0.920	0.883	0.884
Apparel, Leather	0.854	0.821	0.977	0.897	0.874	0.864
Paper Products	0.937	0.947	0.994	0.967	0.944	0.956
Printing, Related Support	0.928	0.928	0.991	0.969	0.935	0.938
Petroleum, Coal	0.944	0.938	0.987	0.959	0.949	0.952
Chemical Products	0.744	0.735	0.976	0.872	0.763	0.788
Plastics, Rubber Products	0.944	0.954	0.990	0.974	0.954	0.969
Durable	0.994	0.993	0.999	0.994	0.995	0.970
Wood Products	0.947	0.946	0.992	0.967	0.954	0.994
Nonmetallic Mineral Products	0.913	0.928	0.992	0.964	0.926	0.959
Primary Metals	0.949	0.953	0.996	0.972	0.953	0.942
Fabricated Metal Products	0.974	0.973	0.997	0.986	0.978	0.959
Machinery	0.971	0.970	0.997	0.984	0.975	0.978
Computers, Electronic Products	0.967	0.965	0.995	0.979	0.974	0.977
Elect. Equip, Appliances, Etc.	0.909	0.885	0.987	0.943	0.921	0.972
Transportation Equipment	0.976	0.976	0.997	0.986	0.979	0.913
Furniture, Related Products	0.940	0.937	0.992	0.966	0.947	0.981
Miscellaneous Manufacturing	0.925	0.936	0.985	0.965	0.935	0.947

Table 3b. Average Annual Correlations across Datasets in Total Hours by Worker Type, Non-mfg.

	Mar/ORG	*Mar/ACS*	*Mar/RAS*	*ORG/ACS*	*ORG/RAS*	*ACS/RAS*
Farms	0.967	0.955	0.996	0.974	0.970	0.963
Forestry, Fishing, Related	0.865	0.867	0.987	0.928	0.879	0.886
Oil, Gas Extraction	0.722	0.657	0.980	0.769	0.750	0.708
Mining, exc. Oil, Gas	0.932	0.925	0.997	0.968	0.937	0.933
Support Activities for Mining	0.879	0.894	0.990	0.944	0.890	0.908
Utilities	0.957	0.953	0.995	0.974	0.962	0.961
Construction	0.996	0.995	1.000	0.997	0.996	0.996
Wholesale	0.987	0.983	0.998	0.989	0.988	0.986
Retail	0.993	0.989	0.999	0.991	0.994	0.991
Air Transportation	0.902	0.895	0.979	0.951	0.920	0.924
Rail Transportation	0.904	0.895	0.996	0.956	0.908	0.908
Water Transportation	0.528	0.450	0.960	0.706	0.541	0.502
Truck Transportation	0.986	0.987	0.999	0.989	0.987	0.988
Transit, Ground Passenger Transp.	0.917	0.923	0.985	0.945	0.927	0.935
Pipeline Transportation	0.402	0.364	0.993	0.451	0.478	0.444
Other Transport and Support	0.968	0.956	0.997	0.978	0.973	0.963
Warehousing and Storage	0.739	0.856	0.977	0.927	0.771	0.879
Publishing Industries	0.926	0.913	0.987	0.937	0.934	0.933
Motion Picture, Sound Recording	0.870	0.865	0.979	0.935	0.886	0.895
Broadcasting, Telecommunications	0.965	0.965	0.992	0.982	0.972	0.974
Information, Data Processing Svc.	0.792	0.684	0.973	0.848	0.822	0.751
Banking, Credit Intermediation	0.981	0.977	0.997	0.986	0.984	0.981
Securities, Commodities, Invest.	0.954	0.957	0.992	0.980	0.962	0.967
Insurance and Related Activities	0.972	0.975	0.996	0.985	0.976	0.980
Funds, Trusts, Other Financial	0.950	0.957	0.991	0.980	0.959	0.966
Real Estate	0.955	0.953	0.990	0.976	0.964	0.964
Rental and Leasing Services	0.858	0.854	0.981	0.907	0.880	0.882
Legal Services	0.973	0.975	0.998	0.986	0.975	0.979
Misc. Prof, Tech, Scientific Services	0.984	0.984	0.997	0.992	0.987	0.988
Computer Systems Design, Related	0.974	0.977	0.995	0.988	0.980	0.983
Management of Companies	0.577	0.338	0.962	0.626	0.602	0.420
Administrative, Support Services	0.982	0.976	0.996	0.981	0.984	0.979
Waste Management, Remediation	0.949	0.918	0.996	0.968	0.954	0.930
Education Services	0.971	0.975	0.994	0.986	0.976	0.980
Ambulatory Health Care Services	0.990	0.987	0.999	0.991	0.991	0.989
Hospitals, Nursing Care Facilities	0.990	0.989	0.998	0.990	0.992	0.990
Social Assistance	0.978	0.976	0.997	0.985	0.981	0.979

Performing Arts, Sports, Museums	0.901	0.883	0.978	0.945	0.920	0.922
Amusements, Gambling, Rec.	0.914	0.918	0.984	0.952	0.929	0.937
Accommodation	0.927	0.929	0.984	0.957	0.941	0.947
Food Services, Drinking Places	0.978	0.979	0.996	0.981	0.980	0.983
Miscellaneous Services	0.985	0.983	0.996	0.990	0.987	0.987

Table 4. Summary of Differences between Potential Datasets

	March CPS	*ACS*	*CPS ORG*
Number of workers per year	63,300	844,500	136,900
Cells that contain <=5 observations	52.1 %	27.5 %	44.0
Potential sources of error in wage measure	Recall error; Hours misreported	Recall error; Hours misreported	Secondary jobs wages not reported; Annualizing current wage rate
Potential sources of error in hours measure	Recall/rounding error;	Recall/rounding error; Daily hours mistaken for weekly	Weeks not reported; Annualizing current hours
Potential sources of error in industry classification	Secondary job industry not reported	Secondary job industry not reported	Assuming no industry changes throughout year
Identification of self-employed workers	Class of worker and business income	Class of worker and business income	Main job self-employed are excluded
When year *T* labor comp index can be estimated	October, *T*+1	November, *T*+2	February, *T*+1

Table 5a. Average Annual % Change in Labor Composition Index, Select Years, Manufacturing

	1987-1995		1995-2000			2000-2009			
	Mar	*ORG*	*Mar*	*ORG*	*RAS*	*Mar*	*ORG*	*ACS*	*RAS*
Manufacturing	0.57	0.57	0.55	0.47	0.66	0.94	0.96	0.94	1.05
Non-Durable	0.78	0.69	0.41	0.45	0.42	0.81	0.73	0.83	0.95
Food, Beverage, Tobacco	1.92	0.72	0.97	0.07	0.95	-0.03	0.58	0.22	0.67
Textile, Textile Products	-0.23	0.42	-0.80	0.64	-1.90	2.23	0.87	0.80	2.09
Apparel, Leather	1.79	1.50	-1.47	-0.06	-0.60	1.85	3.19	1.07	1.29
Paper Products	0.25	0.25	0.50	0.84	2.72	0.68	1.45	0.57	-0.20
Printing, Related Support	1.19	0.72	-0.23	0.52	-0.01	-0.50	0.03	0.60	-0.88
Petroleum, Coal	1.33	-0.58	-3.16	1.29	-7.45	1.62	-0.07	0.01	5.05
Chemical Products	0.91	0.36	-0.50	0.69	-0.87	1.31	0.74	0.69	1.86
Plastics, Rubber Products	1.30	1.13	-0.24	0.24	0.26	0.18	0.43	0.56	0.13
Durable	0.43	0.51	0.47	0.47	0.61	1.08	1.09	1.01	1.19
Wood Products	0.58	0.39	-1.65	0.21	-0.73	1.76	0.86	0.55	-0.19
Nonmetallic Mineral Products	0.23	0.13	0.71	0.01	-0.96	0.83	-0.21	0.45	1.19
Primary Metals	0.24	0.39	2.21	1.92	1.84	0.08	0.31	0.60	-0.57
Fabricated Metal Products	0.20	0.42	1.02	0.79	0.73	1.00	0.40	0.61	0.61
Machinery	0.42	0.45	0.35	0.33	0.69	1.10	1.04	0.73	1.12
Computers, Electronic Products	0.55	0.81	0.65	0.16	0.80	1.53	1.88	1.31	1.61
Elect. Equip, Appliances, Etc.	0.58	0.66	0.48	1.10	-0.29	1.41	0.19	1.31	-0.39
Transportation Equipment	0.17	0.40	0.81	0.52	0.70	1.07	1.27	1.14	1.02
Furniture, Related Products	1.36	0.66	0.24	0.87	1.84	1.25	0.36	0.87	0.32
Miscellaneous Manufacturing	1.67	0.74	-0.82	0.46	-0.27	1.66	1.16	1.20	2.00

Table 5b. Average Annual % Change in Labor Composition Index, Select Years, Non-manufacturing

	1987-1995		1995-2000			2000-2009			
	Mar	*ORG*	*Mar*	*ORG*	*RAS*	*Mar*	*ORG*	*ACS*	*RAS*
Farms	0.49	0.34	0.35	-0.37	0.11	0.07	0.65	-0.04	-0.10
Forestry, Fishing, Related	4.81	-0.14	-4.87	0.69	2.73	3.90	0.46	0.06	0.91
Oil, Gas Extraction	0.10	-0.68	-2.37	-1.47	0.35	4.04	1.25	-1.37	7.84
Mining, exc. Oil, Gas	0.88	0.44	0.34	-1.47	1.69	0.50	0.69	0.28	4.15
Support Activities for Mining	0.38	-0.28	-0.11	-1.12	0.25	-1.48	-1.21	0.54	-7.76
Utilities	0.96	0.57	0.15	0.81	0.75	0.32	0.17	0.35	-0.75
Construction	0.80	0.47	-0.20	0.09	-0.20	0.52	0.47	0.50	0.41
Wholesale	0.48	0.24	1.19	0.27	1.09	0.43	0.41	0.47	0.64
Retail	0.45	0.39	0.26	0.29	0.21	0.20	0.21	0.10	0.28
Air Transportation	0.99	0.47	0.28	0.49	0.57	0.66	0.82	0.92	0.15
Rail Transportation	-0.40	-0.10	-1.08	-0.22	-5.66	0.42	-0.95	0.09	4.64
Water Transportation	0.68	0.09	4.54	2.09	-1.50	-5.07	-2.61	0.26	6.42
Truck Transportation	0.47	0.46	0.33	0.22	0.17	-0.22	-0.01	0.22	-0.62
Transit, Ground Passenger Transp.	0.50	0.51	-0.25	0.52	-1.07	0.79	0.22	0.24	-1.41
Pipeline Transportation	3.24	1.17	0.27	2.91	-1.83	-3.57	1.01	0.61	-18.5
Other Transport and Support	0.49	0.39	1.28	0.14	0.42	0.77	0.52	0.39	2.74
Warehousing and Storage	-1.08	2.18	0.47	3.01	3.61	-0.36	0.10	0.21	1.91
Publishing Industries	1.11	0.53	0.70	0.86	-0.01	1.88	0.81	0.56	1.09
Motion Picture, Sound Recording	-0.07	0.36	-0.81	0.63	-0.37	1.74	0.94	0.64	0.30
Broadcasting, Telecommunications	0.71	0.55	-0.55	-0.28	-0.67	1.01	0.46	0.72	1.02
Information, Data Processing Svc.	1.19	1.03	-0.33	0.57	-0.03	-1.72	-1.82	0.24	2.53
Banking, Credit Intermediation	0.71	0.57	0.01	0.75	-0.07	1.00	0.48	0.86	1.23
Securities, Commodities, Invest.	0.63	0.35	0.13	-0.08	-0.70	1.75	0.75	1.03	1.65
Insurance and Related Activities	0.95	0.75	-0.26	0.23	0.08	0.53	0.26	0.59	0.60

Funds, Trusts, Other Financial	0.89	-0.16	0.35	-0.43	-1.02	1.89	0.49	1.03	1.67
Real Estate	0.68	0.33	-0.12	-0.26	0.43	0.63	0.49	0.42	0.28
Rental and Leasing Services	0.06	-0.54	-0.88	0.10	-1.01	2.27	0.29	0.69	0.94
Legal Services	0.09	0.84	0.55	-0.52	0.88	0.59	0.45	0.34	-0.09
Misc. Prof, Tech, Scientific Services	0.68	0.75	-0.48	0.15	-0.51	0.79	0.60	0.39	0.51
Computer Systems Design, Related	0.89	0.89	0.22	0.24	0.05	0.85	0.82	0.62	0.89
Management of Companies	0.89	-0.16	0.35	-0.43	-1.04	-2.82	-2.26	0.29	3.73
Administrative, Support Services	0.75	0.59	0.29	0.09	0.20	-0.39	-0.13	0.26	-0.62
Waste Management, Remediation	1.10	0.78	-0.62	0.02	-0.75	-0.19	0.76	-0.10	-1.72
Education Services	-0.18	0.29	0.34	-0.03	0.38	0.72	0.30	0.23	0.69
Ambulatory Health Care Services	-0.38	-0.44	-0.71	-0.47	-0.67	-0.09	0.02	-0.38	-0.13
Hospitals, Nursing Care Facilities	0.61	0.73	0.77	0.43	0.85	0.31	0.58	0.55	0.32
Social Assistance	-0.45	-0.15	0.90	0.26	1.46	0.33	0.43	0.72	0.07
Performing Arts, Sports, Museums	1.16	0.15	-1.12	0.67	-0.15	-0.21	0.76	0.16	-0.95
Amusements, Gambling, Recreation	-0.13	0.82	-0.07	0.14	1.04	0.18	0.50	0.21	0.13
Accommodation	0.38	0.16	0.12	0.49	-0.58	0.77	0.34	0.30	1.32
Food Services, Drinking Places	0.41	0.52	-0.11	0.06	-0.39	0.52	0.27	0.32	0.30
Miscellaneous Services	0.46	0.48	0.46	0.40	0.41	-0.14	0.01	0.14	0.00

Table 6a. Average Annual Change in MFP with Inclusion of Labor Composition, Manufacturing

	1987-1995		1995-2000			2000-2009			
	Mar	*ORG*	*Mar*	*ORG*	*RAS*	*Mar*	*ORG*	*ACS*	*RAS*
Manufacturing	-0.28	-0.20	-0.18	-0.22	-0.18	-0.31	-0.29	-0.21	-0.32
Non-Durable	-0.34	-0.20	-0.04	-0.14	-0.06	-0.21	-0.21	-0.17	-0.29
Food, Beverage, Tobacco	-0.29	-0.11	-0.16	0.00	-0.14	-0.02	-0.10	-0.06	-0.11
Textile, Textile Products	0.05	-0.10	0.20	-0.16	0.48	-0.59	-0.22	-0.19	-0.61
Apparel, Leather	-0.58	-0.46	0.32	0.02	0.08	-0.34	-1.13	-0.34	-0.41
Paper Products	-0.09	-0.05	-0.12	-0.18	-0.62	-0.17	-0.31	-0.10	0.03
Printing, Related Support	-0.41	-0.24	0.08	-0.16	0.00	0.18	-0.01	-0.14	0.30
Petroleum, Coal	-0.16	0.05	0.16	-0.10	0.32	-0.03	0.00	0.03	-0.14
Chemical Products	-0.19	-0.07	0.06	-0.14	0.14	-0.24	-0.13	-0.08	-0.34
Plastics, Rubber Products	-0.36	-0.29	0.06	-0.04	-0.06	-0.02	-0.10	-0.17	-0.03
Durable	-0.14	-0.20	-0.22	-0.18	-0.20	-0.42	-0.36	-0.27	-0.32
Wood Products	-0.13	-0.10	0.36	-0.04	0.16	-0.47	-0.24	-0.11	0.03
Nonmetallic Mineral Products	-0.13	-0.06	-0.22	-0.02	0.28	-0.26	0.08	-0.14	-0.36
Primary Metals	-0.06	-0.10	-0.60	-0.48	-0.50	0.00	-0.06	-0.10	0.10
Fabricated Metal Products	-0.09	-0.16	-0.32	-0.26	-0.22	-0.28	-0.12	-0.10	-0.19
Machinery	-0.14	-0.15	-0.08	-0.08	-0.18	-0.36	-0.33	-0.20	-0.36
Computers, Electronic Products	-0.19	-0.26	-0.20	-0.02	-0.26	-0.61	-0.76	-0.38	-0.66
Elect. Equip, Appliances, Etc.	-0.20	-0.21	-0.12	-0.26	0.06	-0.38	-0.06	-0.30	0.10
Transportation Equipment	-0.08	-0.10	-0.24	-0.16	-0.20	-0.26	-0.31	-0.28	-0.26
Furniture, Related Products	-0.50	-0.25	-0.12	-0.30	-0.68	-0.40	-0.12	-0.31	-0.10
Miscellaneous Manufacturing	-0.54	-0.24	0.30	-0.16	0.10	-0.57	-0.41	-0.32	-0.69

Table 6b. Average Annual Change in MFP with Inclusion of Labor Composition, Non-manufacturing

	1987-1995		1995-2000			2000-2009			
	Mar	*ORG*	*Mar*	*ORG*	*RAS*	*Mar*	*ORG*	*ACS*	*RAS*
Farms	-0.06	-0.08	-0.08	-0.06	-0.02	0.00	-0.17	0.02	0.02
Forestry, Fishing, Related	-1.91	0.10	1.92	-0.26	-1.10	-2.12	-0.31	0.03	-0.43
Oil, Gas Extraction	-0.02	0.11	0.40	0.18	-0.04	-0.56	-0.14	0.10	-0.86
Mining, exc. Oil, Gas	-0.24	-0.15	-0.32	0.42	-0.74	-0.21	-0.17	-0.11	-0.74
Support Activities for Mining	-0.65	0.13	0.66	0.48	-0.12	0.38	0.30	-0.20	2.21
Utilities	-0.19	-0.10	-0.02	-0.14	-0.12	-0.04	-0.02	-0.09	0.16
Construction	-0.31	-0.19	0.10	-0.02	0.12	-0.21	-0.19	-0.19	-0.17
Wholesale	-0.24	-0.13	-0.60	-0.14	-0.54	-0.19	-0.22	-0.20	-0.27
Retail	-0.23	-0.19	-0.12	-0.18	-0.08	-0.09	-0.07	-0.04	-0.12
Air Transportation	-0.31	-0.15	-0.10	-0.16	-0.18	-0.22	-0.26	-0.18	-0.01
Rail Transportation	0.10	0.05	0.44	0.06	1.82	-0.08	0.28	-0.02	-2.19
Water Transportation	-0.14	-0.01	-0.62	-0.30	0.16	0.80	0.41	-0.07	-1.93
Truck Transportation	-0.23	-0.21	-0.14	-0.08	-0.06	0.06	-0.01	-0.07	0.26
Transit, Ground Passenger Transp.	-0.21	-0.21	0.12	-0.24	0.56	-0.46	-0.11	-0.13	0.79
Pipeline Transportation	-0.59	-0.28	-0.78	-0.58	0.66	0.67	0.00	-0.06	0.02
Other Transport and Support	-0.30	-0.26	-0.72	-0.08	-0.26	-0.43	-0.29	-0.28	-1.14
Warehousing and Storage	0.70	-1.60	-0.14	-2.60	-2.46	0.20	-0.10	-0.11	-1.12
Publishing Industries	-0.40	-0.18	-0.20	-0.30	0.06	-0.60	-0.23	-0.16	-0.36
Motion Picture, Sound Recording	0.08	-0.18	0.32	-0.22	0.08	-0.83	-0.41	-0.30	-0.08
Broadcasting, Telecommunications	-0.20	-0.18	0.18	0.10	0.20	-0.24	-0.11	-0.13	-0.22
Information, Data Processing Svc.	-0.63	-0.53	0.20	-0.24	0.02	0.72	0.68	-0.13	0.03
Banking, Credit Intermediation	-0.26	-0.23	-0.02	-0.22	0.02	-0.31	-0.16	-0.28	-0.39

Securities, Commodities, Invest.	-0.38	-0.30	-0.22	0.02	0.30	-0.93	-0.40	-0.32	-0.90
Insurance and Related Activities	-0.53	-0.41	0.16	-0.18	-0.08	-0.28	-0.10	0.12	-0.29
Funds, Trusts, Other Financial	-0.08	0.05	-0.04	0.02	0.08	-0.17	-0.06	-0.06	-0.16
Real Estate	-0.08	-0.01	-0.02	0.00	-0.06	-0.03	-0.03	-0.03	-0.01
Rental and Leasing Services	-0.04	0.09	0.14	0.00	0.16	-0.22	-0.02	-0.07	-0.08
Legal Services	-0.11	-0.59	-0.36	0.36	-0.60	-0.37	-0.29	-0.29	0.08
Misc. Prof, Tech, Scientific Services	-0.58	-0.60	-0.12	-0.16	-0.04	-0.54	-0.50	-0.34	-0.56
Computer Systems Design, Related	-0.50	-0.56	0.30	-0.10	0.30	-0.48	-0.37	-0.19	-0.30
Management of Companies	-0.51	0.10	-0.24	0.22	0.52	1.84	1.39	-0.31	-0.76
Administrative, Support Services	-0.43	-0.34	-0.18	-0.08	-0.14	0.27	0.10	-0.20	0.41
Waste Management, Remediation	-0.43	-0.29	0.20	0.00	0.26	0.10	-0.22	0.03	0.56
Education Services	0.00	-0.04	-0.02	0.00	-0.02	-0.11	-0.08	-0.04	-0.11
Ambulatory Health Care Services	0.20	0.25	0.40	0.24	0.36	0.04	-0.04	0.14	0.06
Hospitals, Nursing Care Facilities	-0.20	-0.21	-0.22	-0.12	-0.22	-0.09	-0.16	-0.11	-0.08
Social Assistance	0.15	0.04	-0.38	-0.10	-0.58	-0.16	-0.21	-0.26	-0.03
Performing Arts, Sports, Museums	-0.80	-0.10	0.70	-0.40	0.06	-0.01	-0.42	0.01	0.40
Amusements, Gambling, Recreation	0.00	-0.38	0.04	-0.08	-0.38	-0.07	-0.20	-0.10	-0.07
Accommodation	-0.16	-0.08	-0.04	-0.18	0.24	-0.29	-0.09	-0.08	-0.47
Food Services, Drinking Places	-0.16	-0.20	0.06	-0.02	0.16	-0.20	-0.11	-0.10	-0.13
Miscellaneous Services	-0.21	-0.24	-0.22	-0.20	-0.20	0.08	0.00	-0.03	0.00

Table 7. Average Annual Change in MFP with Inclusion of Aggregated Labor Composition, Transportation Industries and Farms, Forestry, Fishing and Related

	1987-1995		1995-2000			2000-2009			
	Mar	*ORG*	*Mar*	*ORG*	*RAS*	*Mar*	*ORG*	*ACS*	*RAS*
Farms	-0.04	-0.04	-0.20	0.00	0.20	0.03	-0.08	0.02	0.04
Forestry, Fishing, Related	-0.25	-0.13	-0.30	0.00	0.60	0.13	-0.34	0.07	0.24

Air Transportation	-0.15	-0.15	0.50	0.20	0.50	-0.04	-0.09	-0.07	-0.01
Rail Transportation	-0.19	-0.24	0.50	0.10	0.50	-0.07	-0.11	-0.07	-0.03
Water Transportation	-0.06	-0.09	0.20	0.10	0.20	-0.03	-0.03	-0.01	-0.03
Truck Transportation	-0.18	-0.20	0.70	0.20	0.70	-0.08	-0.16	-0.10	-0.06
Transit, Ground Passenger Transp.	-0.19	-0.20	0.70	0.20	0.70	-0.11	-0.19	-0.13	-0.09
Pipeline Transportation	-0.08	-0.06	0.20	0.00	0.20	-0.01	-0.07	-0.04	0.00
Other Transport and Support	-0.25	-0.31	0.70	0.10	0.70	-0.11	-0.20	-0.12	-0.08
Warehousing and Storage	-0.26	-0.35	0.70	0.10	0.70	-0.11	-0.18	-0.13	-0.09

Figure 1a. MFP With and Without Inclusion of Labor Composition, Manufacturing

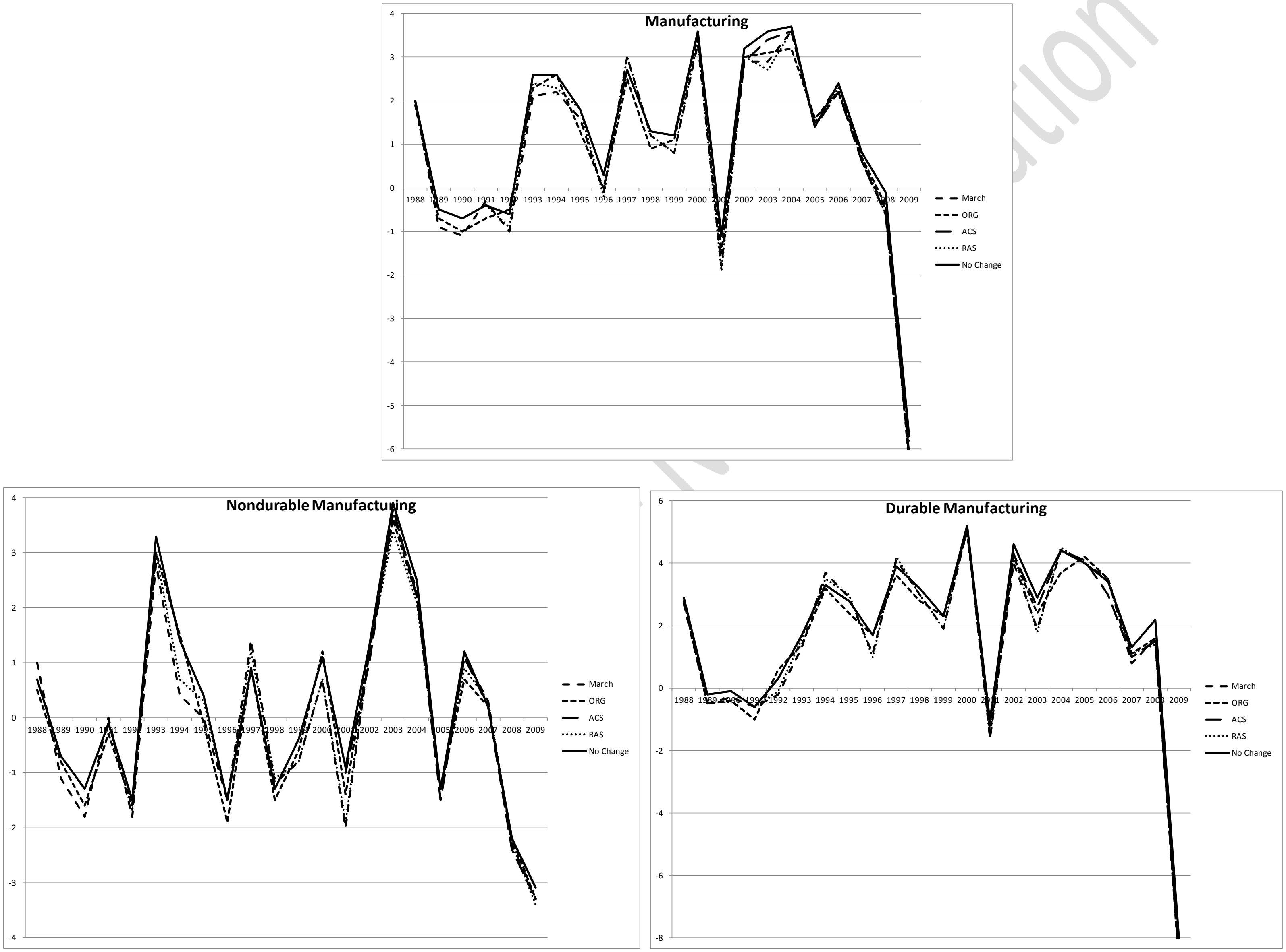
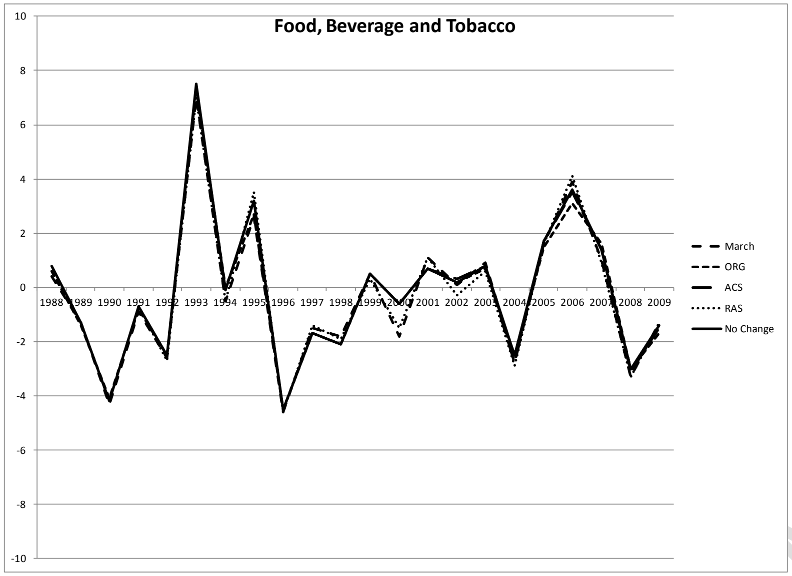
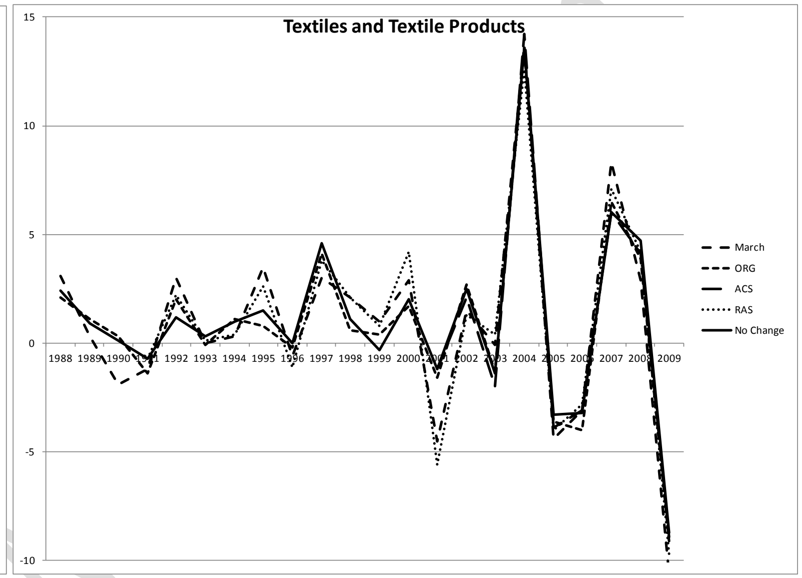
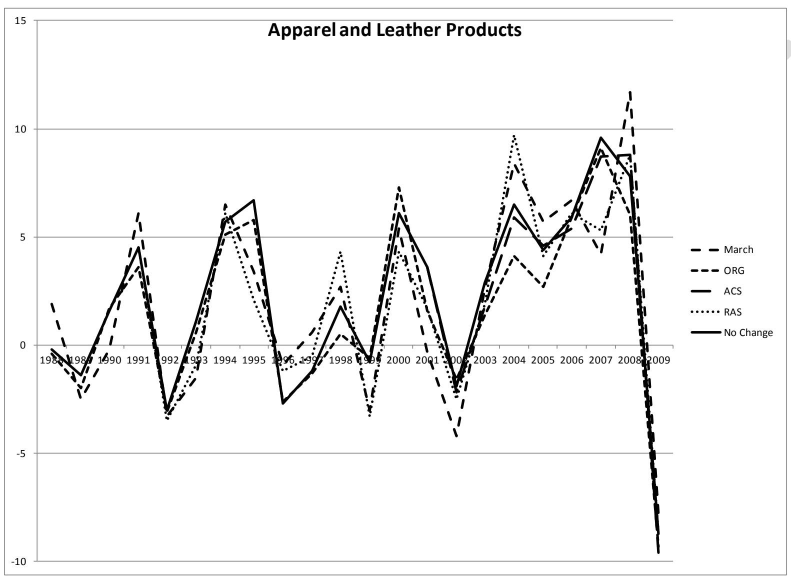


Figure 1a (cont'd)







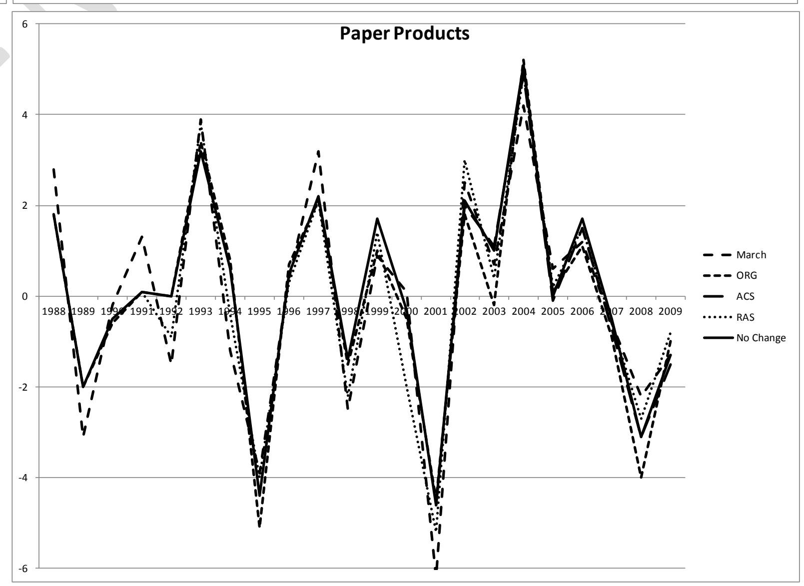
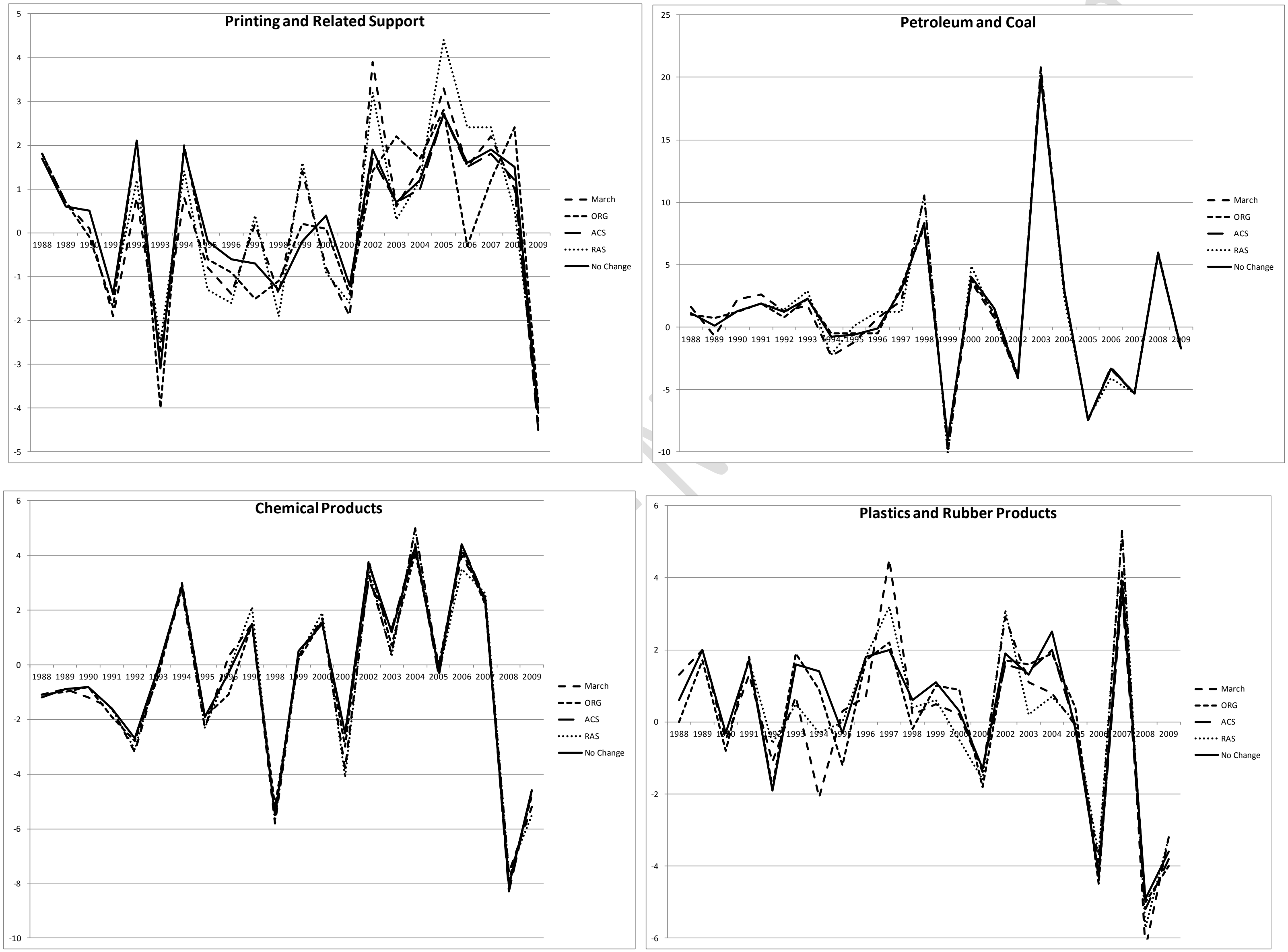
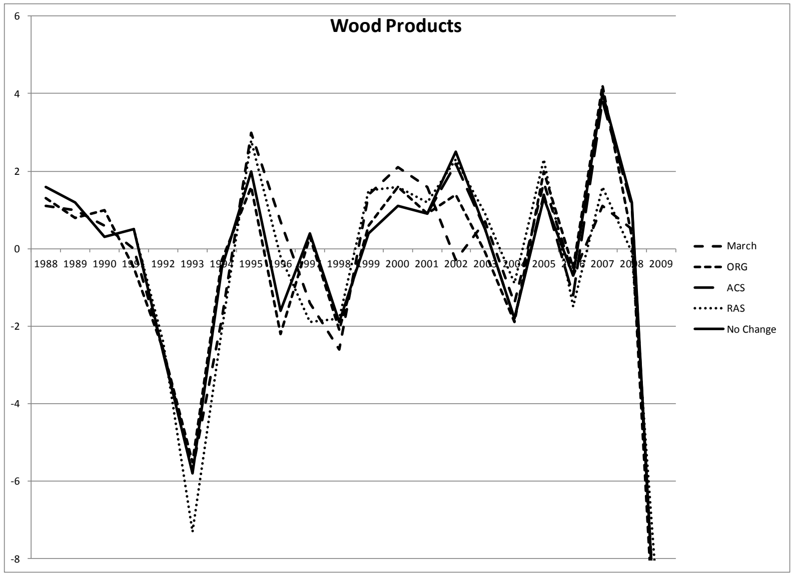
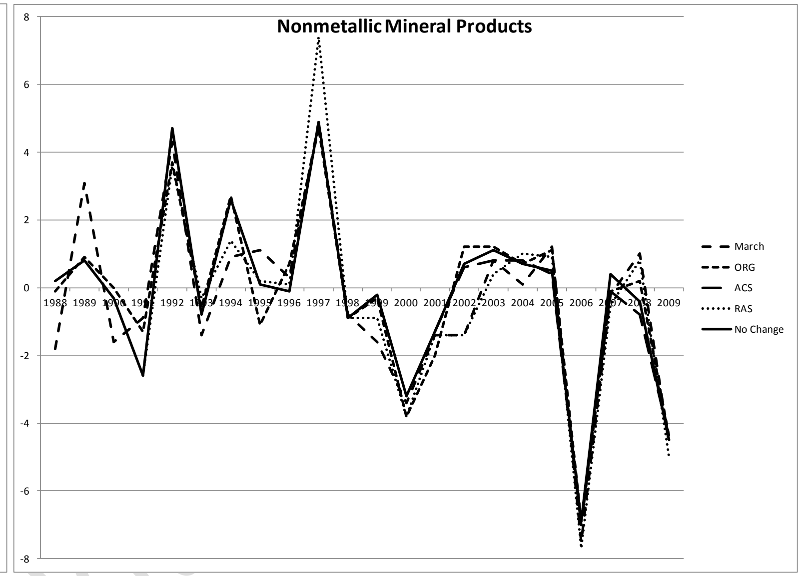
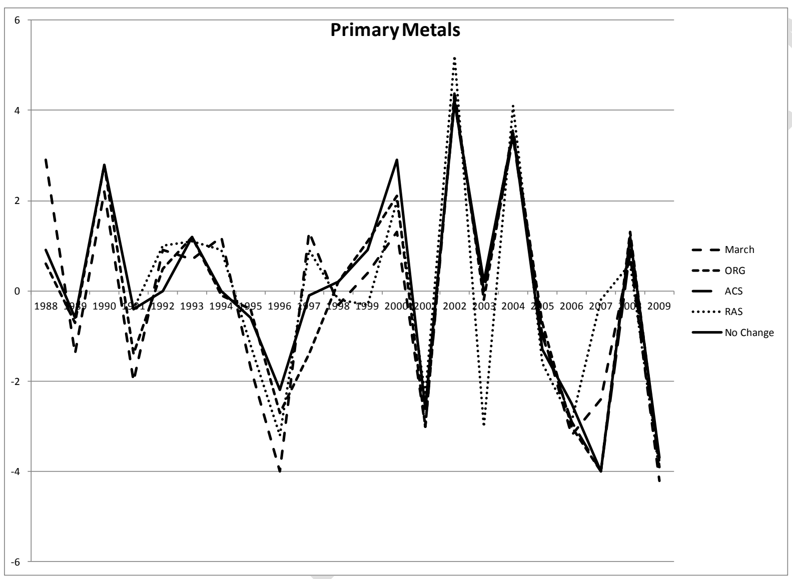


Figure 1a (cont'd)




Wood Products
March
ORG
ACS
RAS
No Change


Nonmetallic Mineral Products
March
ORG
ACS
RAS
No Change


Primary Metals
March
ORG
ACS
RAS
No Change

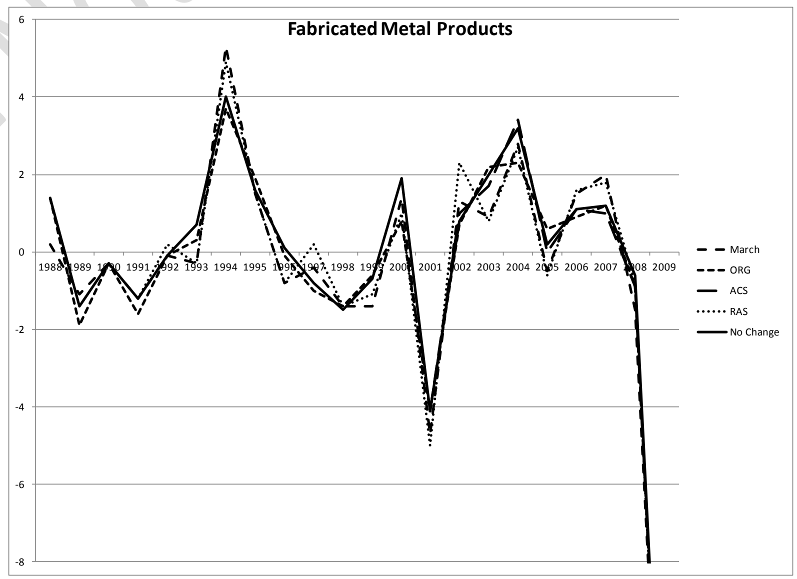
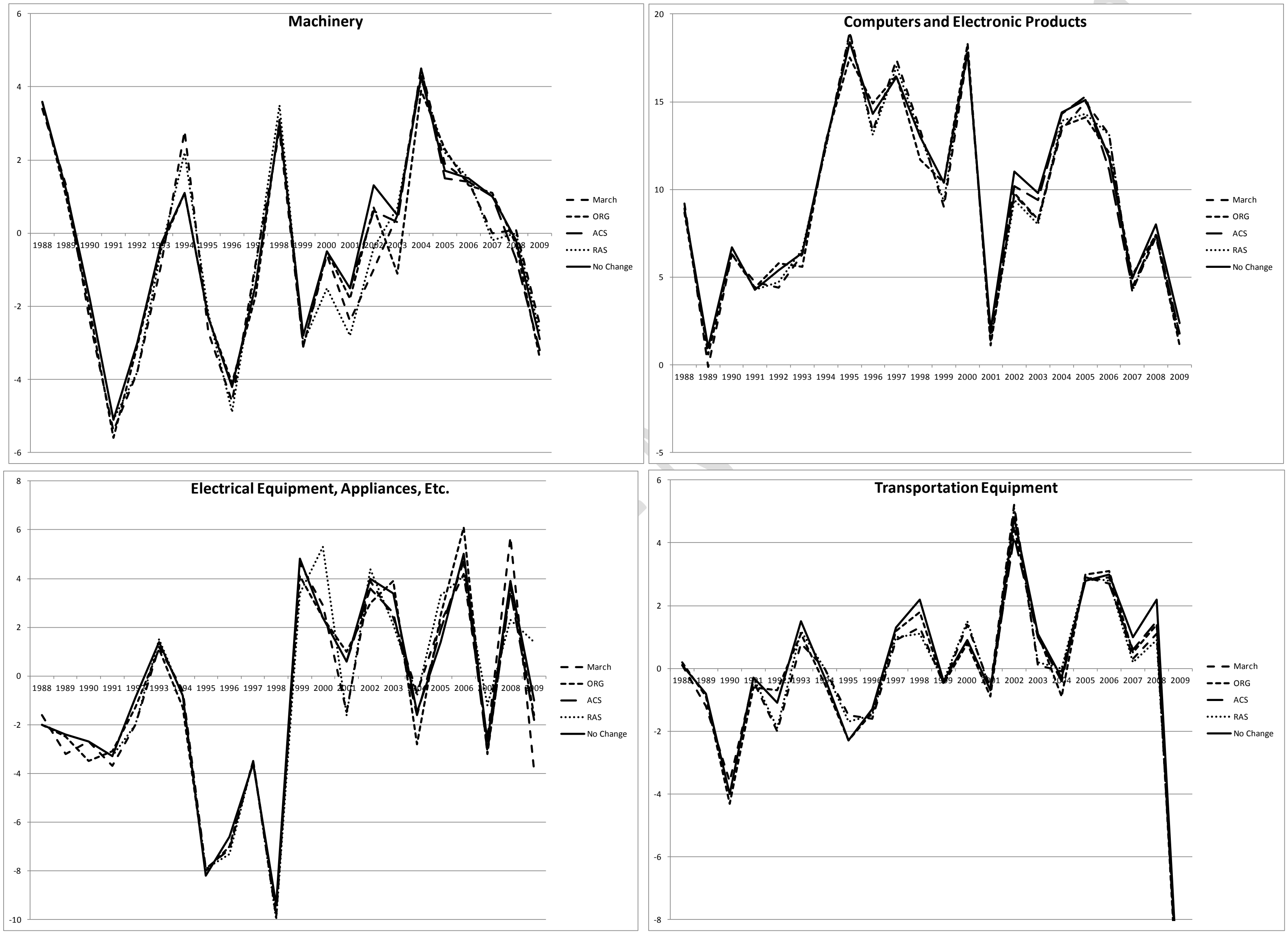

Fabricated Metal Products
March
ORG
ACS
RAS
No Change

Figure 1a. (cont'd)



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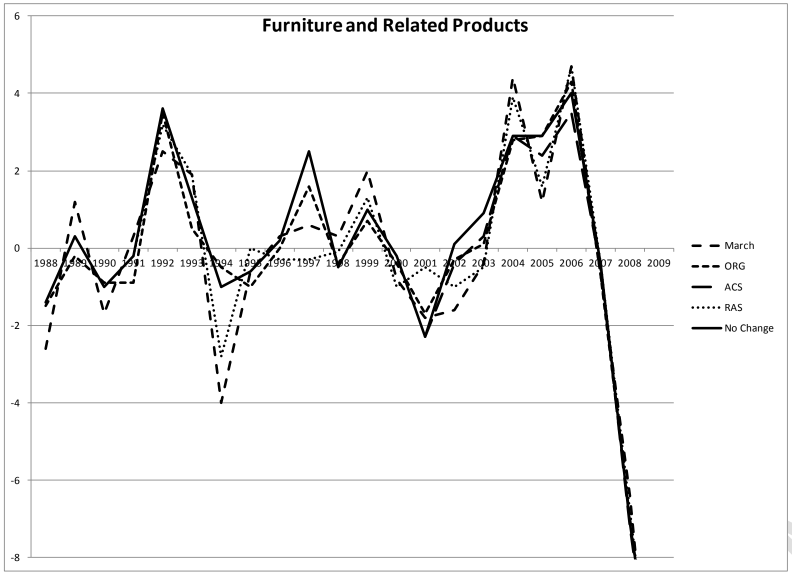


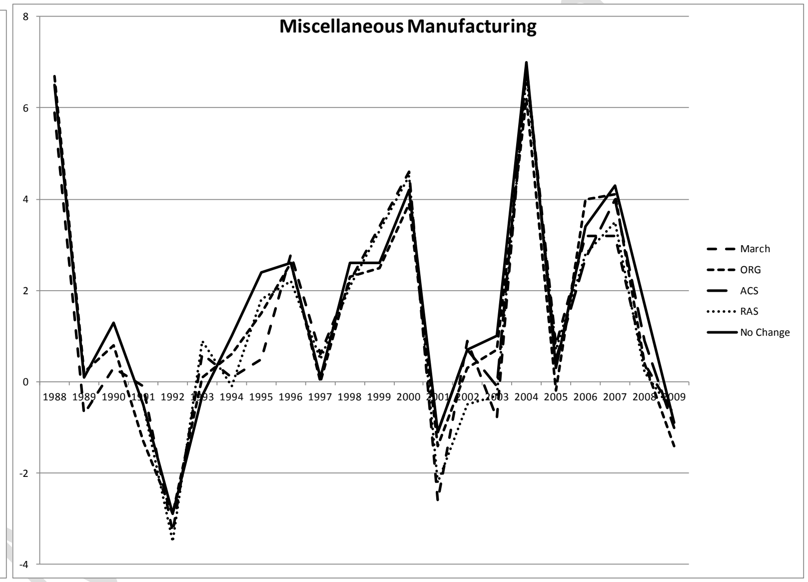
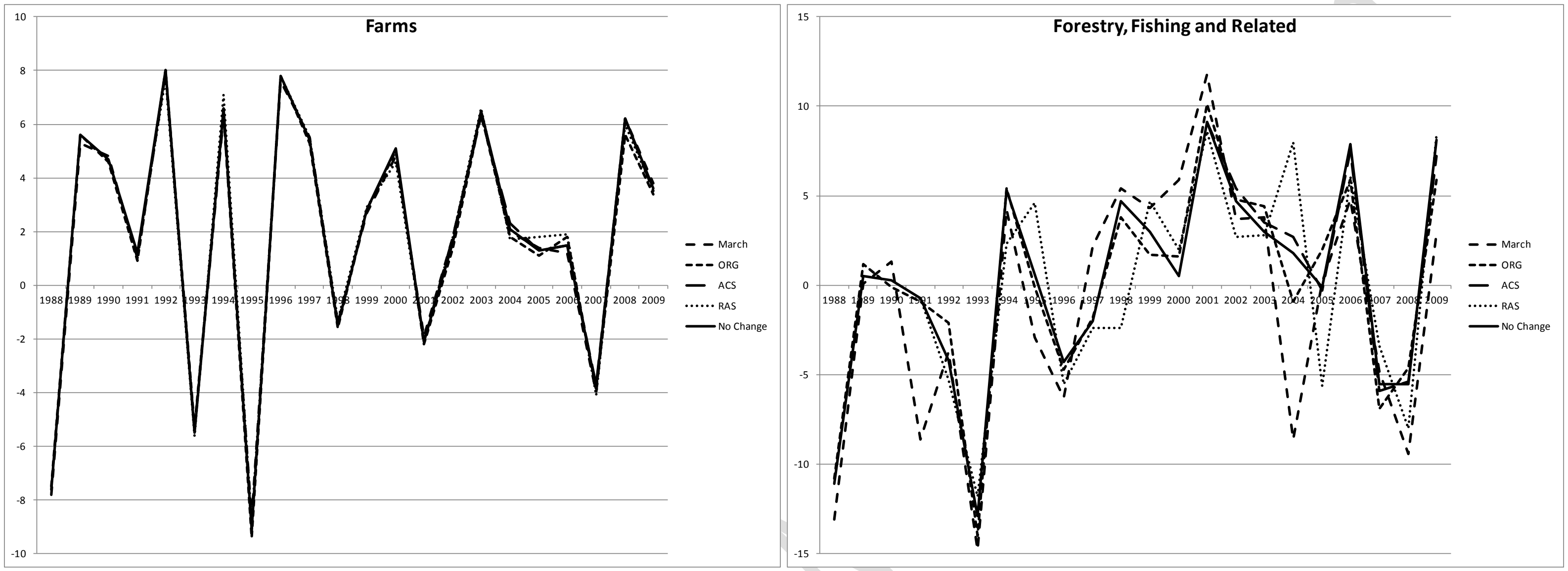


Figure 1b. MFP With and Without Inclusion of Labor Composition, Nonmanufacturing



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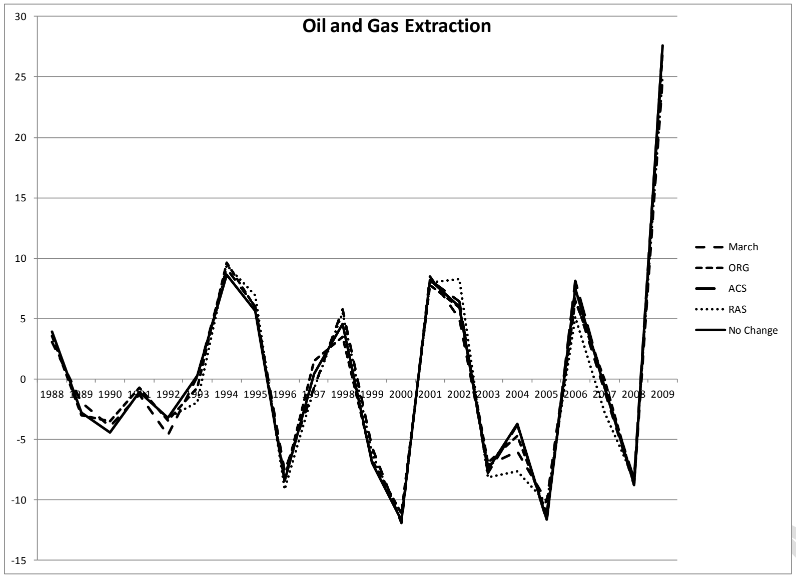

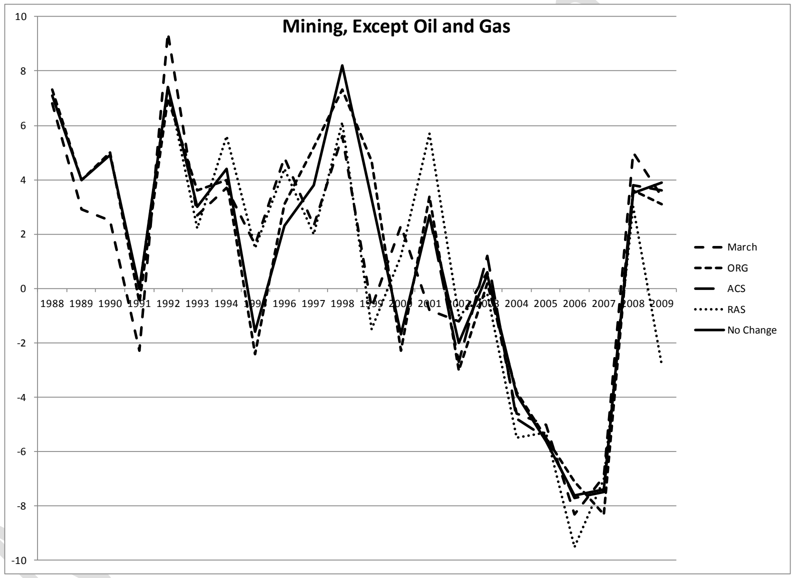

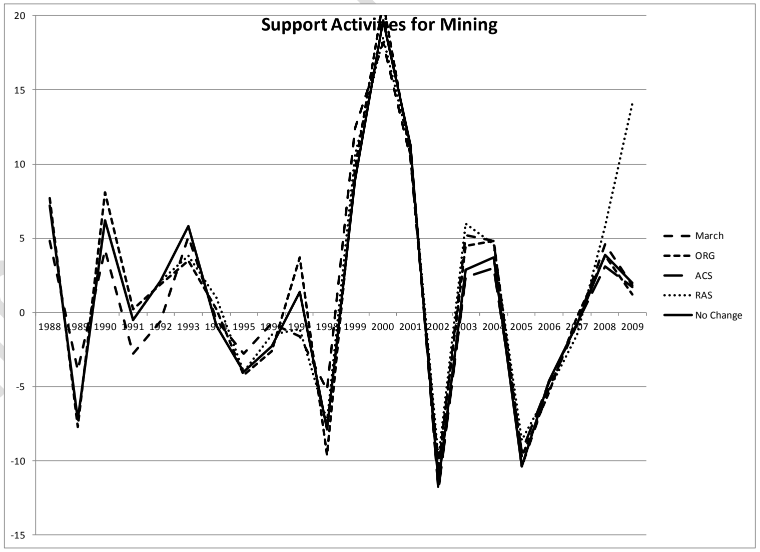

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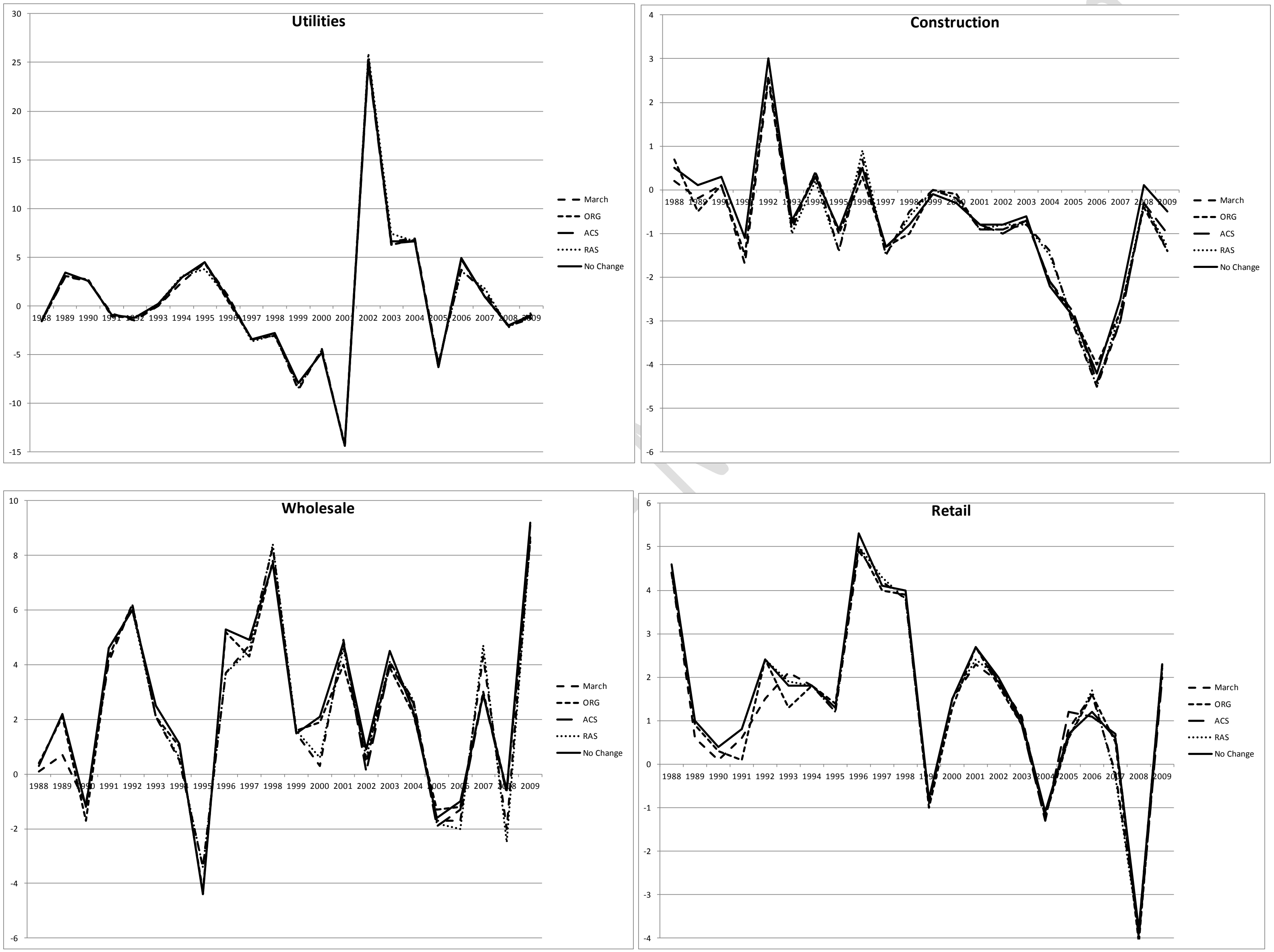

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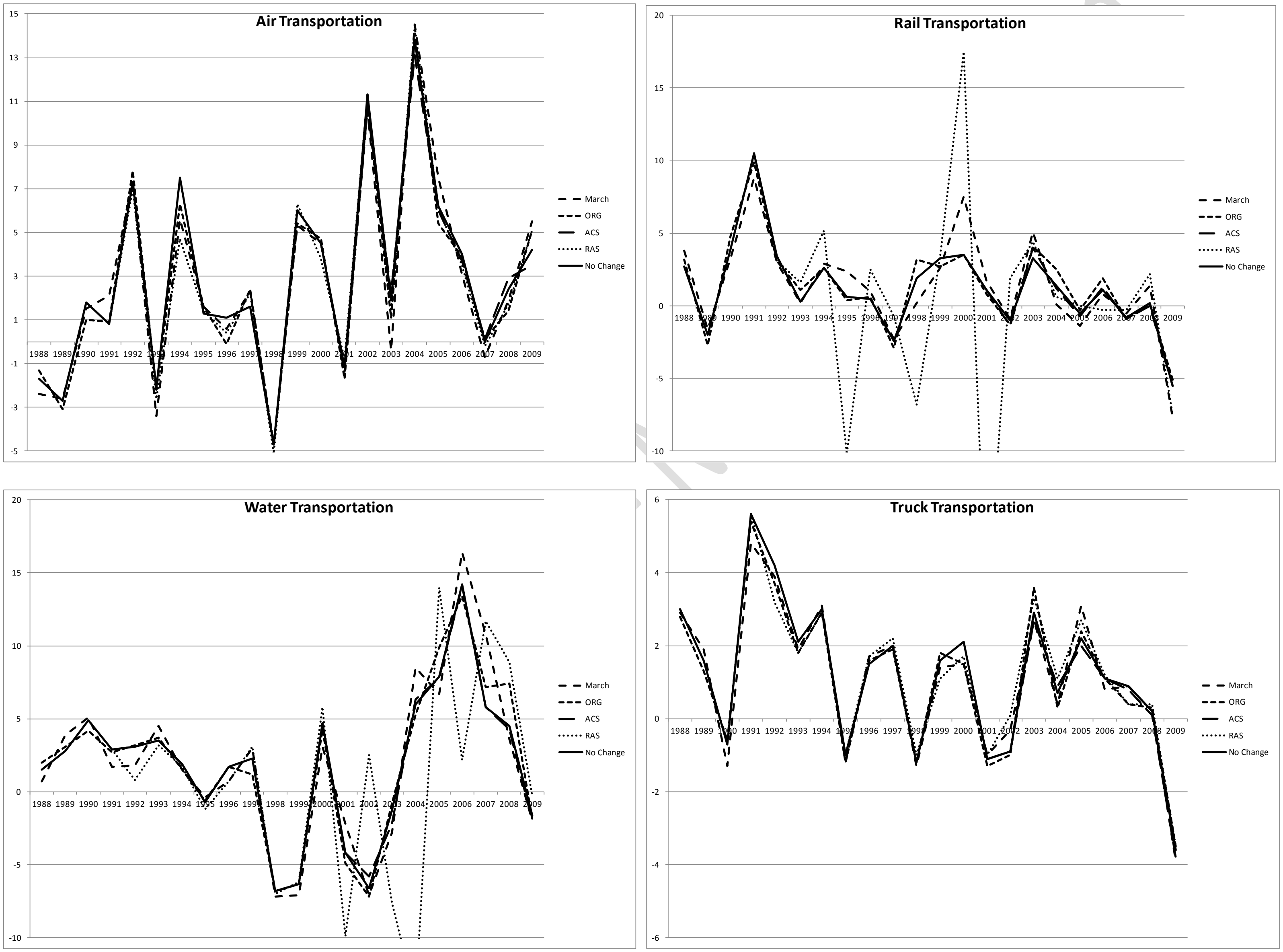

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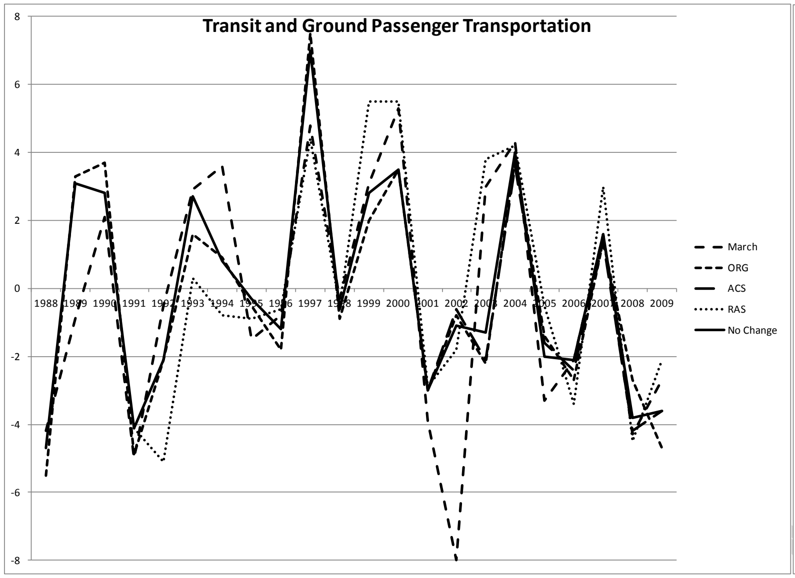

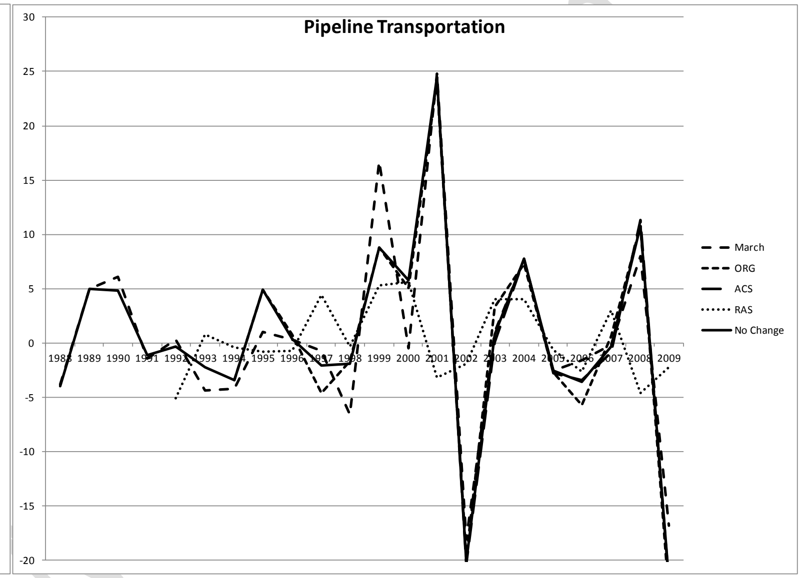

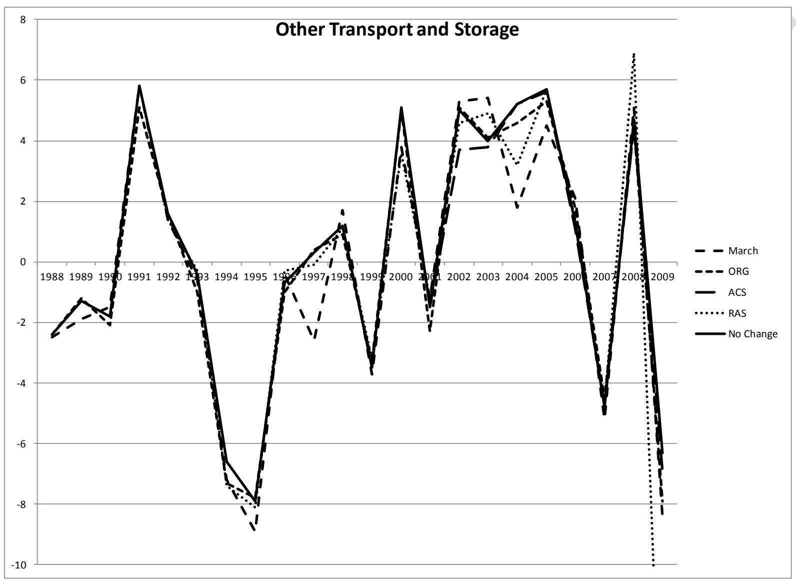

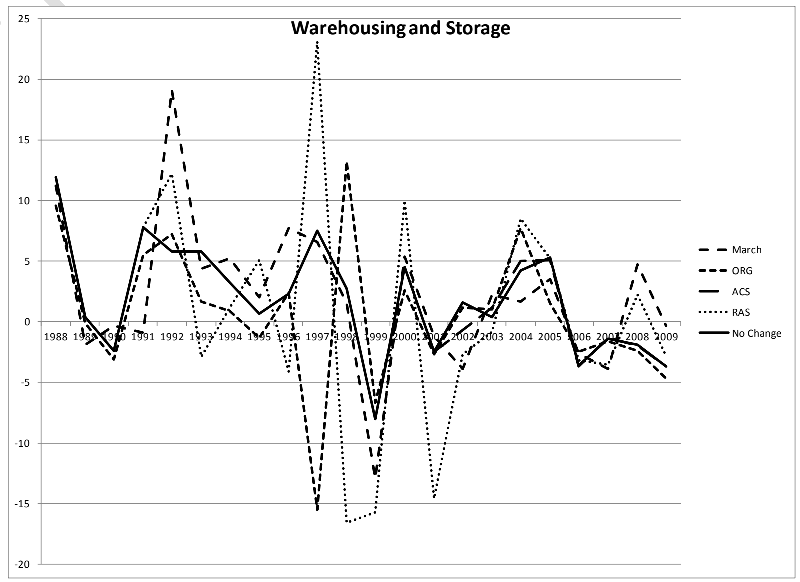

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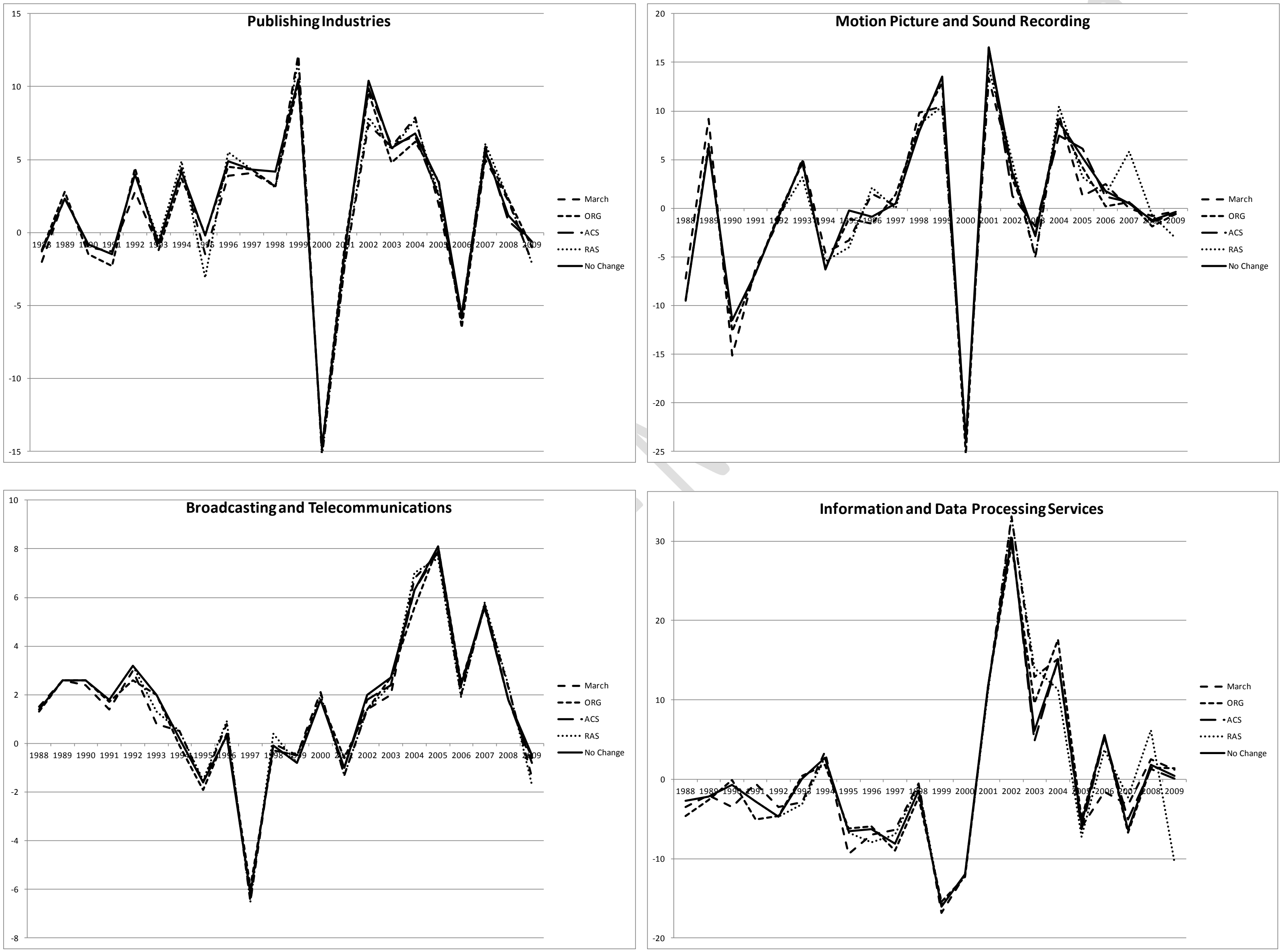

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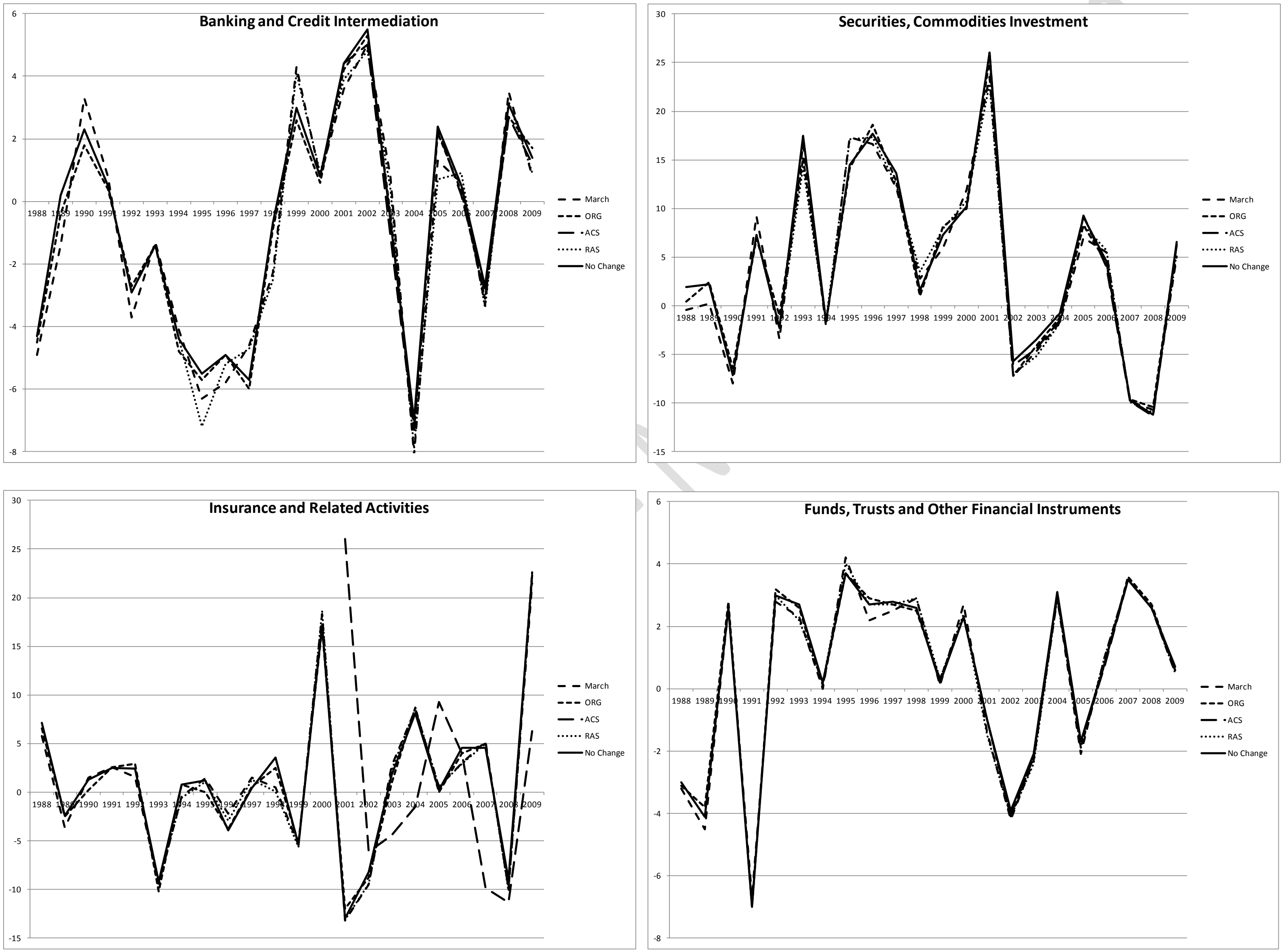

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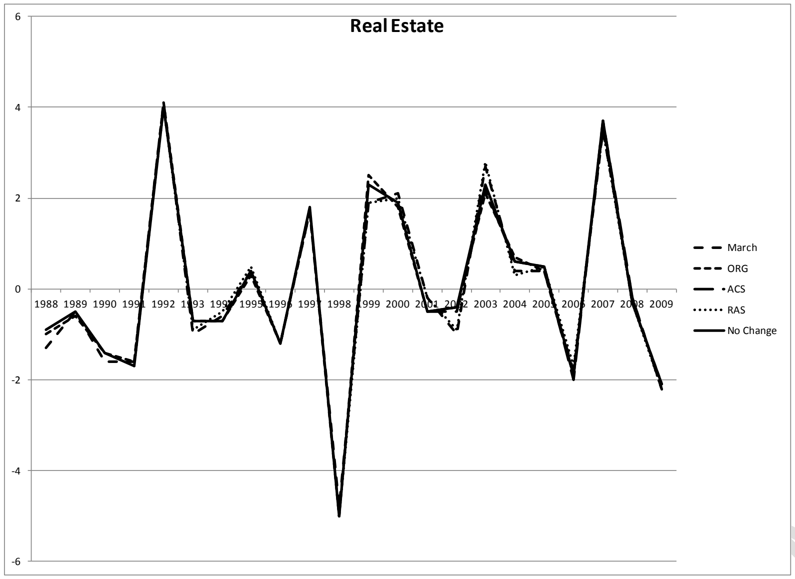

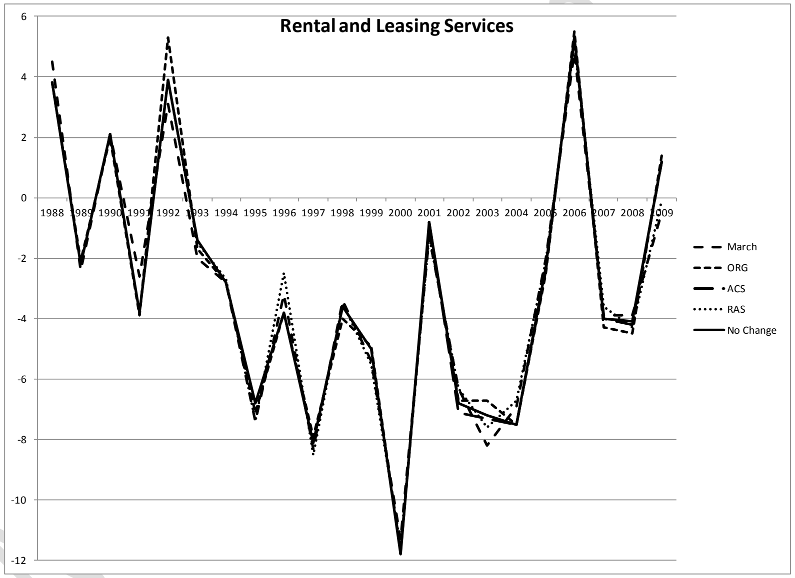

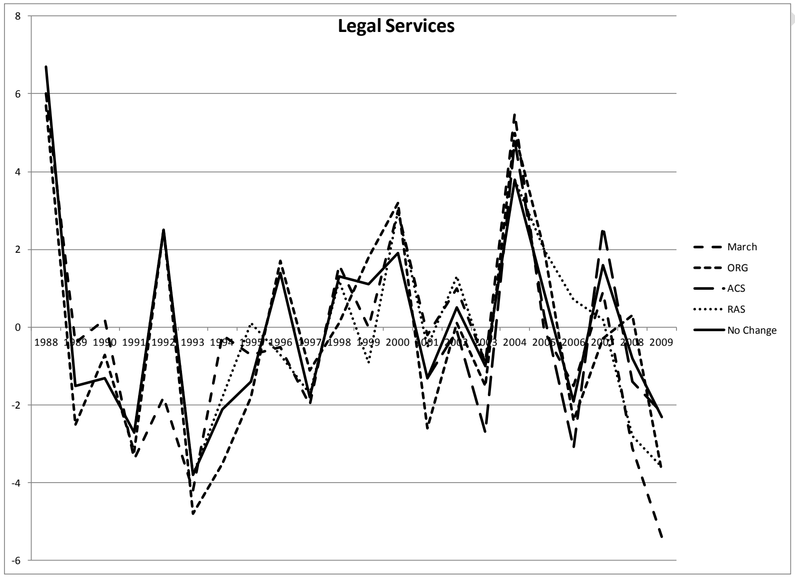

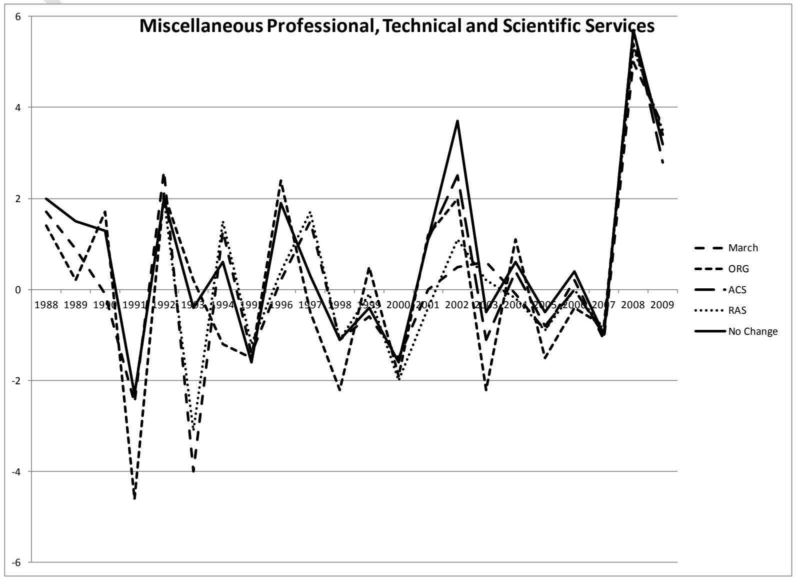

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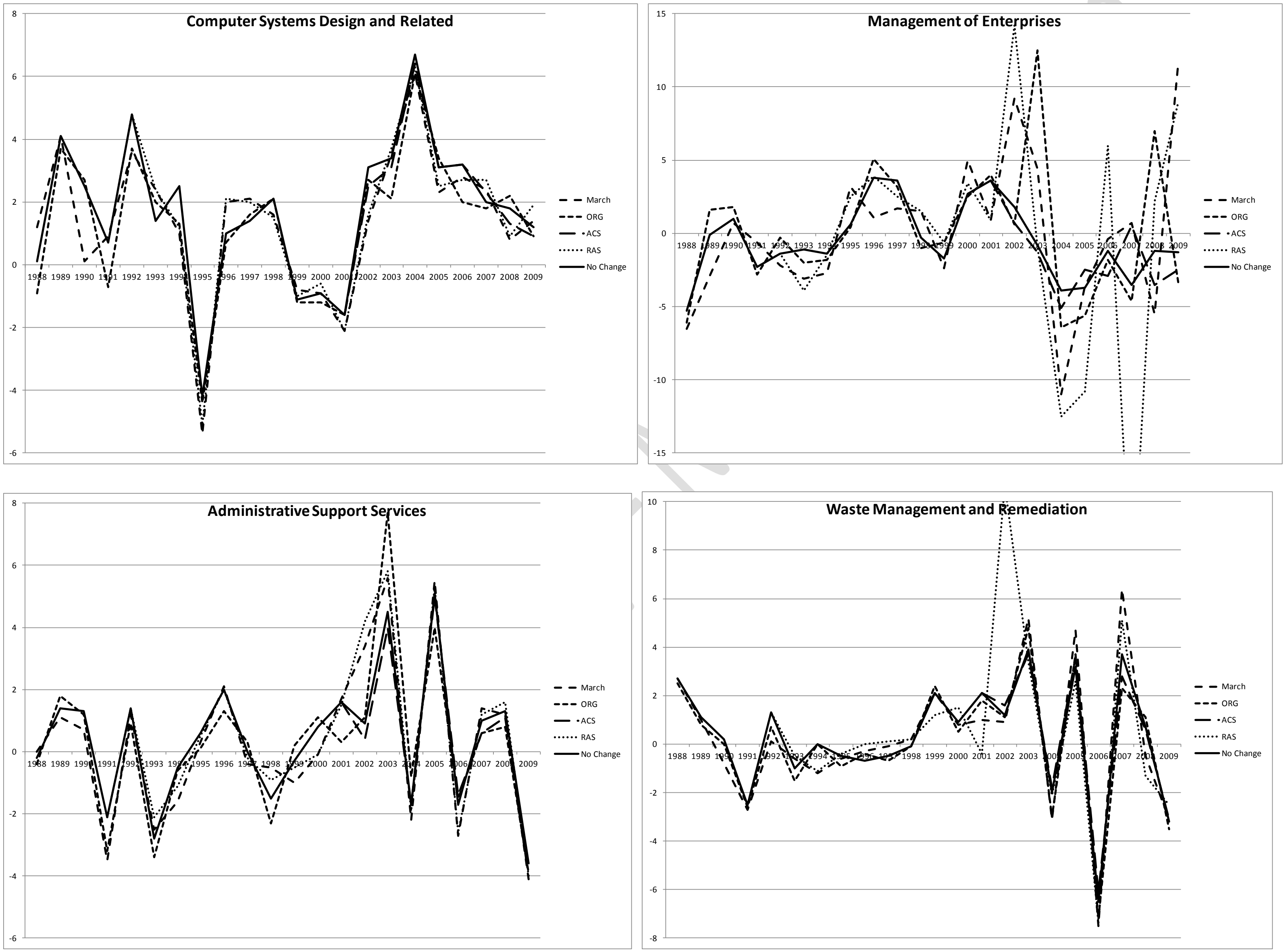

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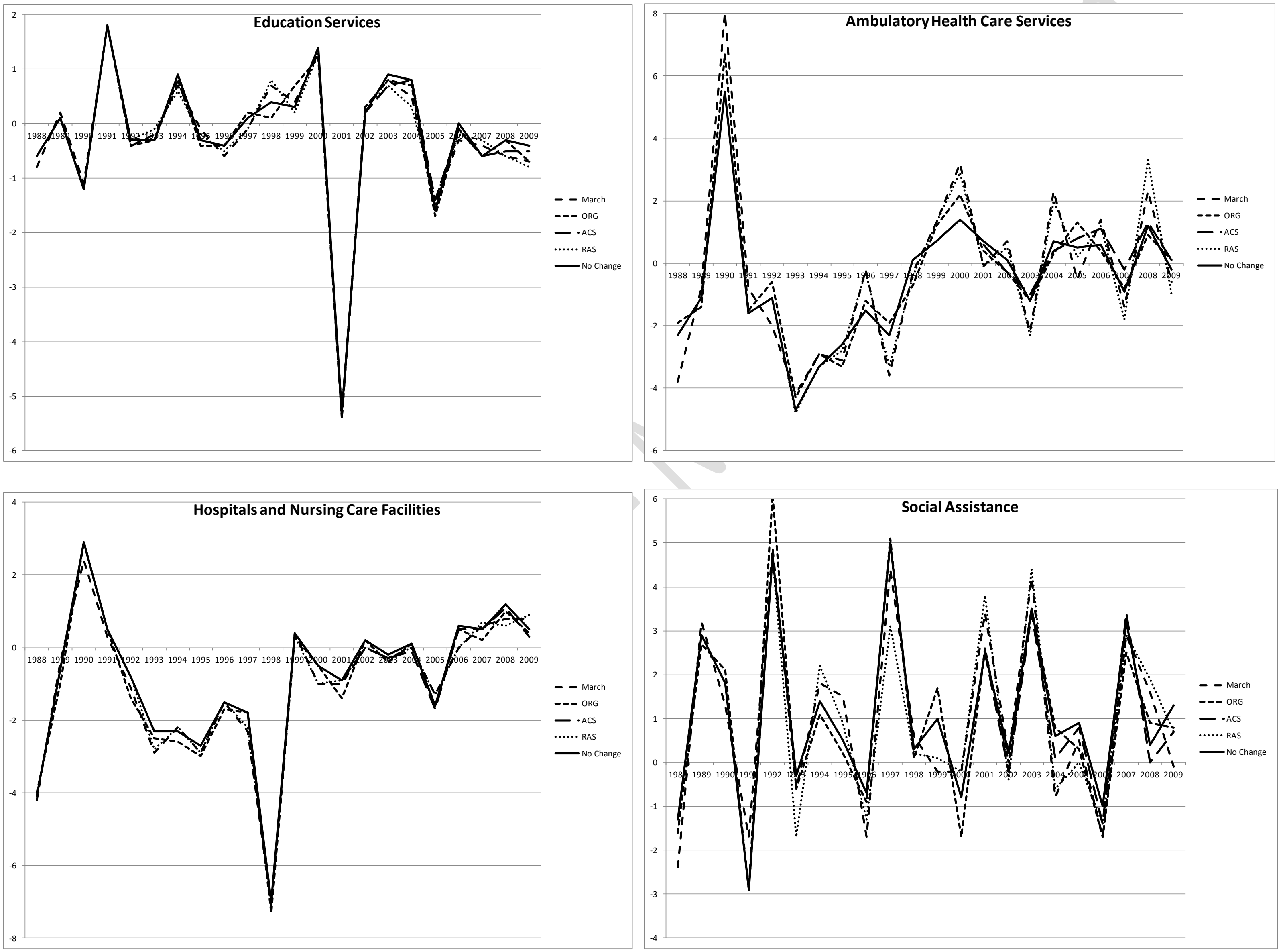

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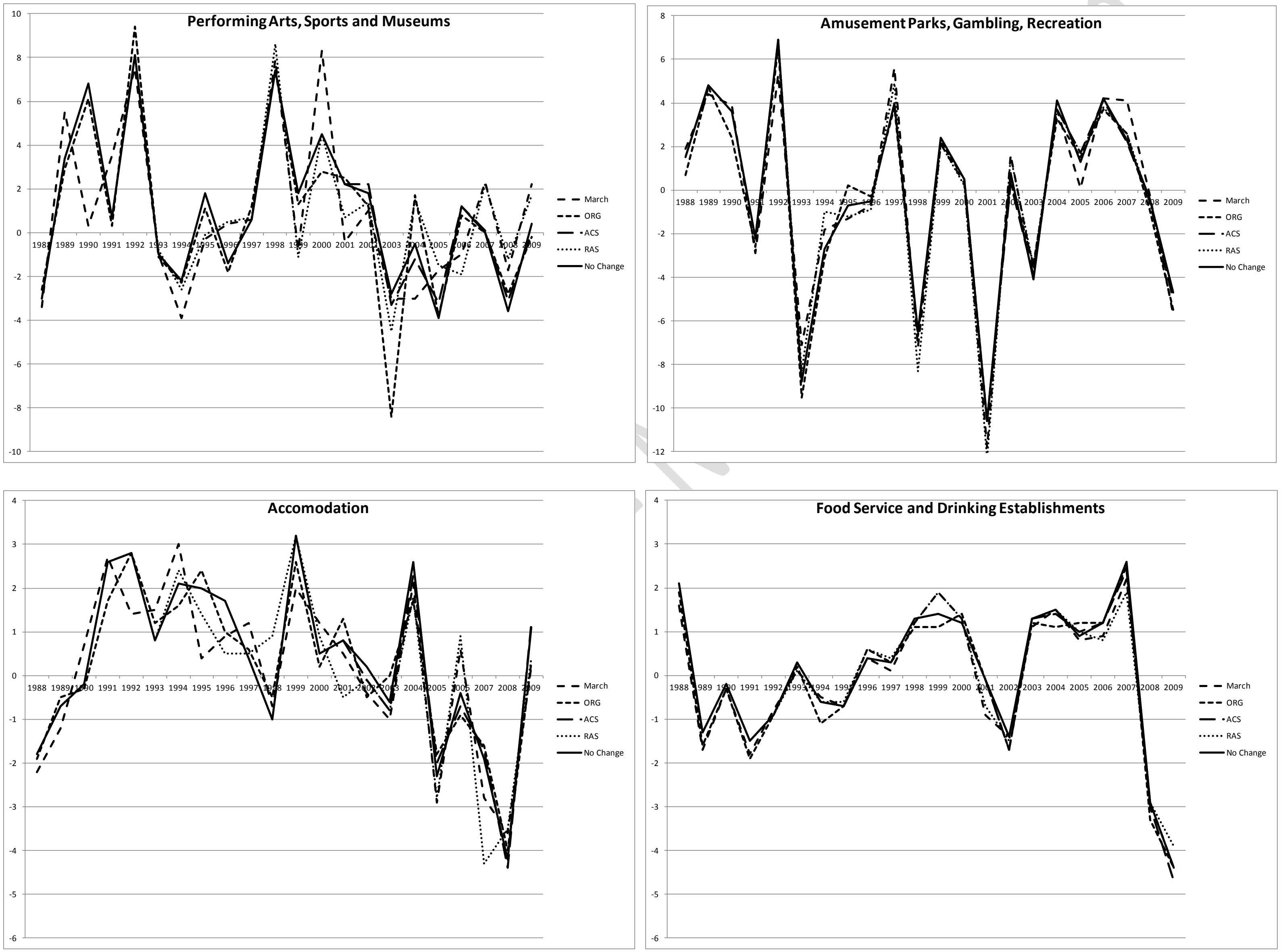

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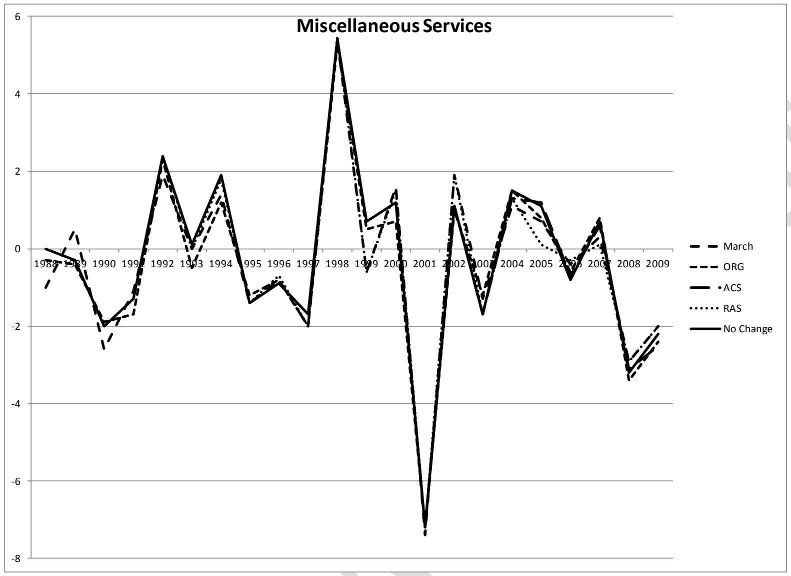
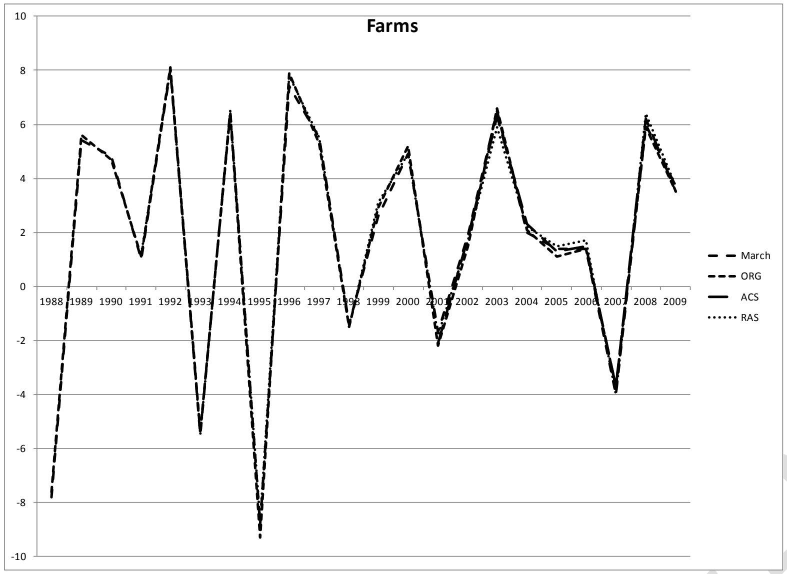


Figure 1c. MFP with Aggregated Labor Composition Indexes for Farms and Fishing and for Transportation



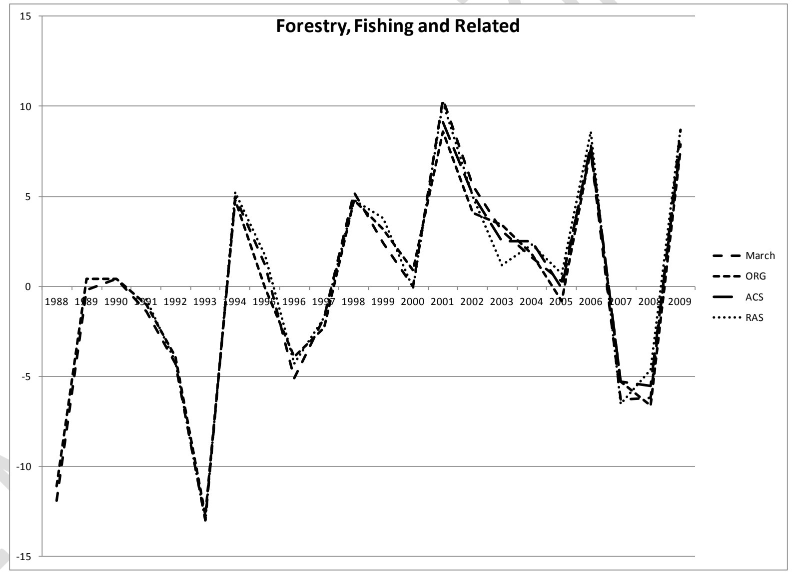


Figure 1c, cont'd

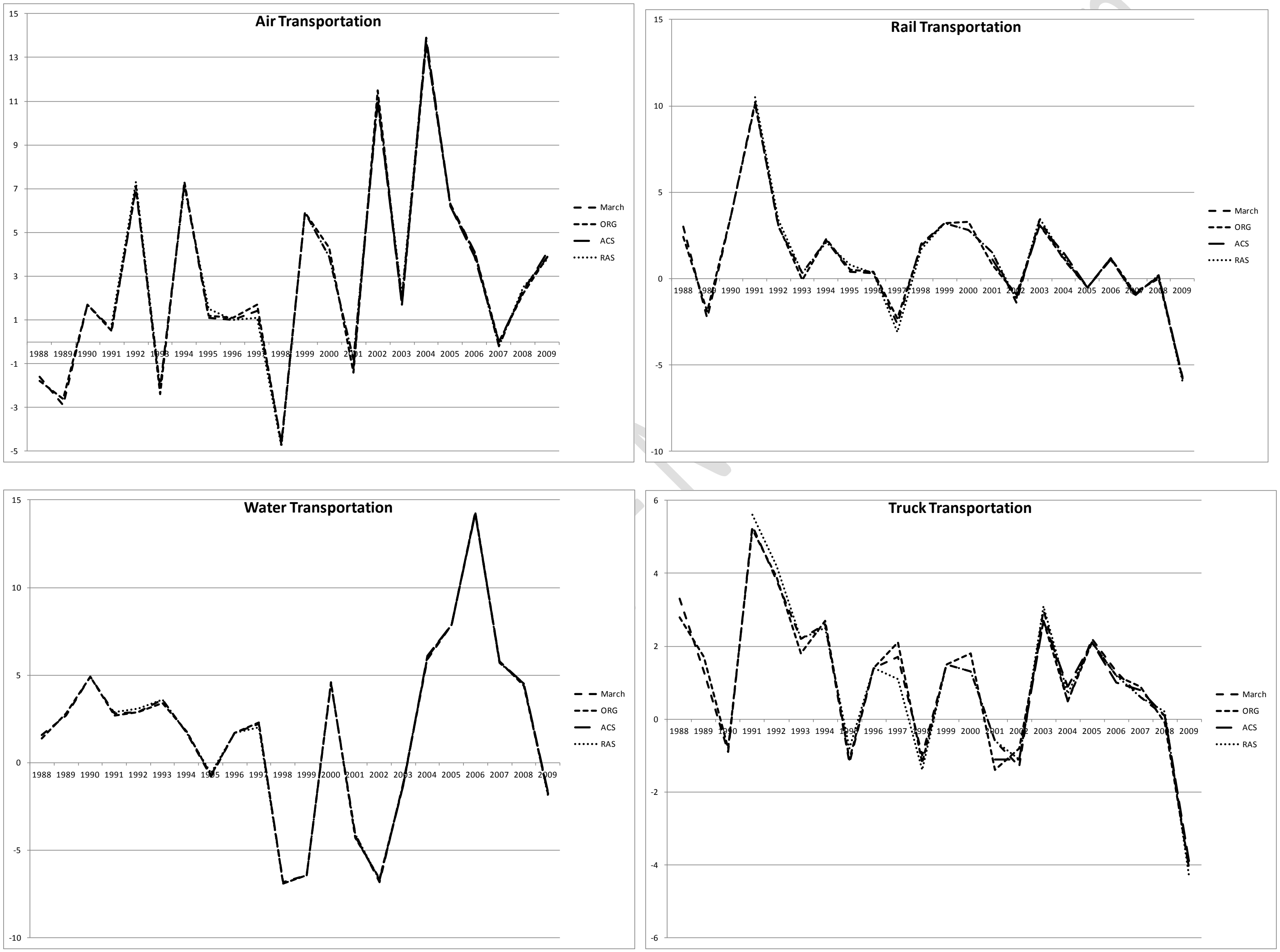
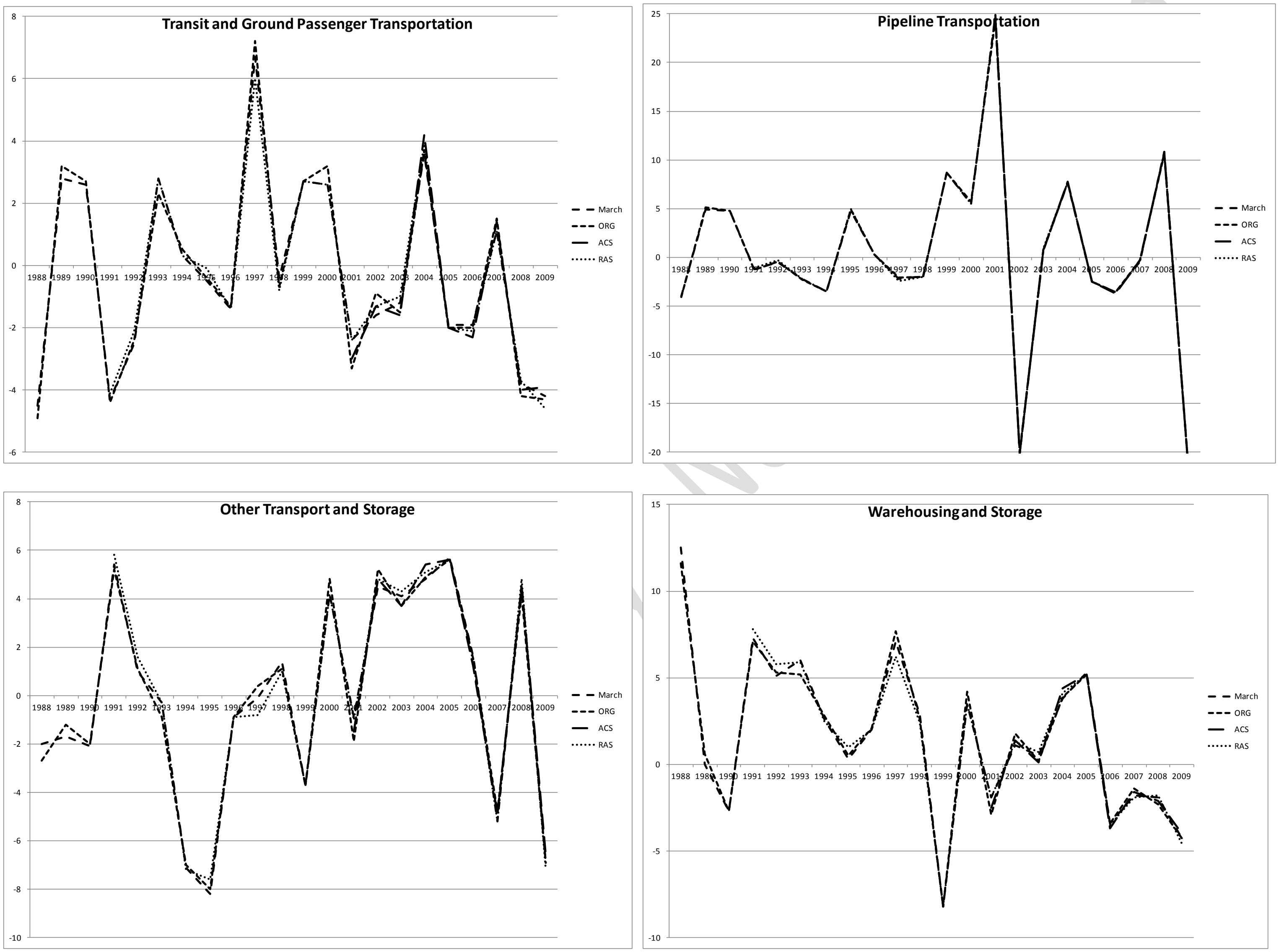


Figure 1c, cont'd



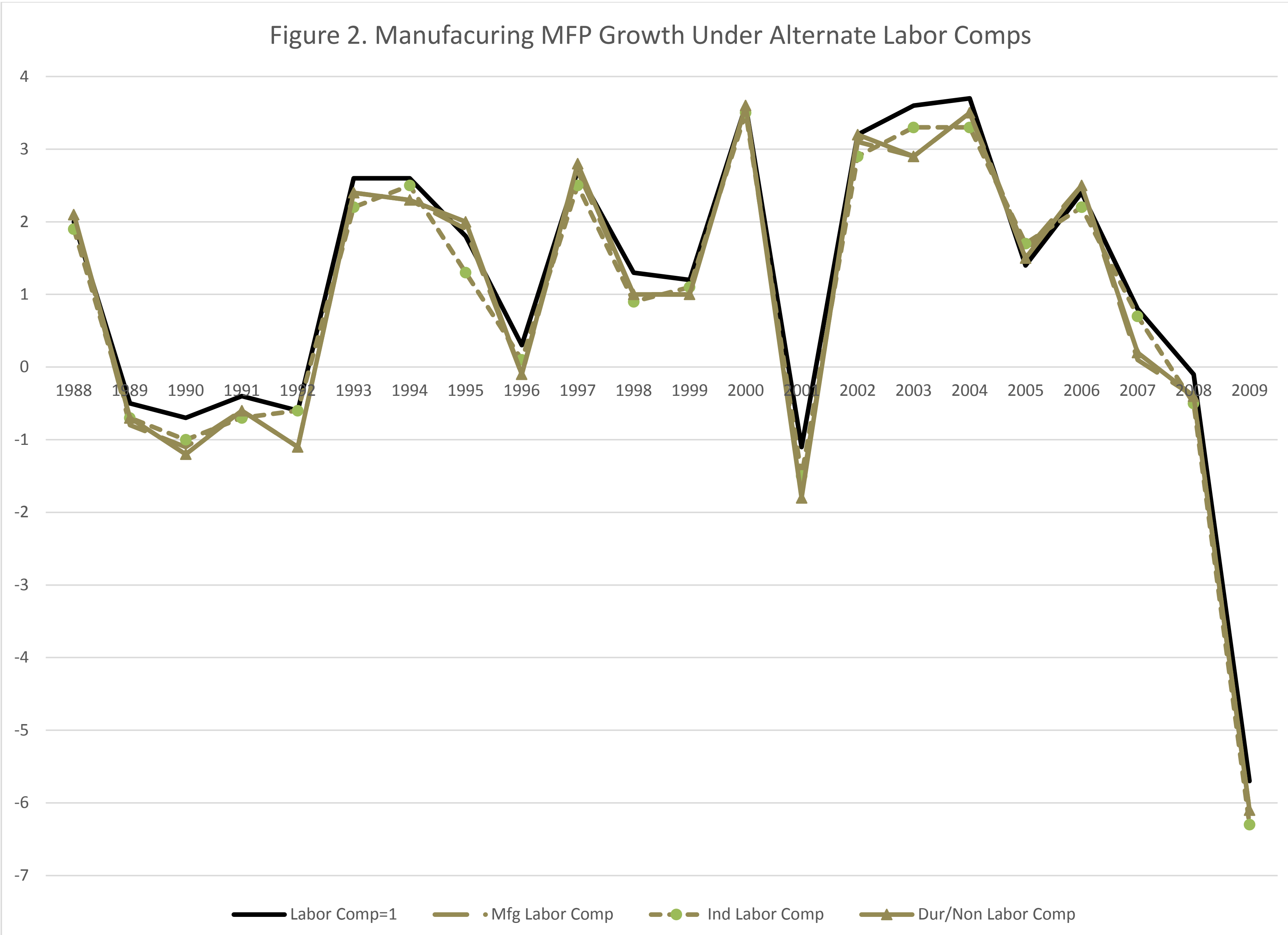


Figure 2. Manufacuring MFP Growth Under Alternate Labor Comps
4
3
2
1
0
-1
-2
-3
-4
-5
-6
-7
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Labor Comp=1
Mfg Labor Comp
Ind Labor Comp
Dur/Non Labor Comp

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