Using Efficiency Tests to Reduce Revisions in Panel Data: The Case of Wage and Salary Estimates for U.S. States

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Abstract

This paper studies the preliminary estimates of state wage and salary growth produced by the U.S. Bureau of Economic Analysis (BEA), investigating whether they may be improved using basic efficiency tests. State wage and salary growth can be thought of as the sum of two components, an aggregate component equal to the currently prevailing national growth rate, and a state specific component, which we call the idiosyncratic variation in the estimates. BEA currently uses extrapolation techniques to compute the idiosyncratic component of the preliminary estimates, and this paper demonstrates some limitations to this approach. While revisions to BEA's preliminary numbers are currently predictable, some simple regression-based generalizations of the extrapolation approach can reduce this predictability, cutting down mean squared and mean absolute revisions. While these reductions in revisions are not large, we can reject at conventional significance levels the hypothesis that they are equal to zero.

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This paper studies the preliminary estimates of state wage and salary growth produced by the U.S. Bureau of Economic Analysis (BEA), investigating whether they may be improved using basic efficiency tests. State wage and salary growth can be thought of as the sum of two components, an aggregate component equal to the currently prevailing national growth rate, and a state specific component, which we call the idiosyncratic variation in the estimates. BEA currently uses extrapolation techniques to compute the idiosyncratic component of the preliminary estimates, and this paper demonstrates some limitations to this approach. While revisions to BEA's preliminary numbers are currently predictable, some simple regression-based generalizations of the extrapolation approach can reduce this predictability, cutting down mean squared and mean absolute revisions. While these reductions in revisions are not large, we can reject at conventional significance levels the hypothesis that they are equal to zero.

At the heart of the approach taken in this paper is the most basic version of an efficiency test, essentially a test of whether the preliminary wage and salary estimates would be better predictors of subsequent wage and salary estimates (based on superior information not available at the time of the preliminary estimates) if they were re-scaled by some factor or set of factors. These type of tests have become routine in applied time series econometrics, especially in the literature on forecasting; however few papers focus on generalizing and applying these tests to panel data. This paper does so, working in a context where our panel of growth rates is controlled to a national growth rate, and where any modifications to the preliminary growth rates must leave the national growth rate unaltered. Hence the paper focuses on testing the efficiency of and improving the purely idiosyncratic variation in our panel of preliminary estimates.

I. Data and Revisions

BEA reports its first quarterly estimate of state-level growth rates of wages and salaries, the preliminary $\Delta\mathrm{WS}^{p}_{i,t}$, in its initial report on state personal income, generally released 4 months after the end of the quarter. Here the t subscript on $\Delta\mathrm{WS}^{p}$ indexes quarters, and i indexes states. BEA's second estimate, $\Delta\mathrm{WS}^{s}_{i,t}$, is released 3 months later. The second estimate and all subsequent BEA estimates are based largely on wage and salary data from the Bureau of Labor Statistic's (BLS)'s ES-202 program (also called the Covered Employment and Wages program); we will call the BEA's most recent version of this data its "latest" version, $\Delta\mathrm{WS}^{l}_{i,t}$.[1] The Bureau of Labor Statistics (BLS) reports the ES-202 data that it receives from each state, on the total employment and wage disbursements of the entire universe of businesses whose employees are covered by the unemployment insurance system of the United States. The BLS Handbook of Methods (2003) estimates that this universe encompasses about 97 percent of total U.S. nonfarm payrolls.

The ES-202 data are not available when BEA releases its first quarterly estimate of wage and salary growth, $\Delta\mathrm{WS}^{p}_{i,t}$; for this reason BEA relies heavily on available state-level data from the BLS's Current Employment Statistics (CES) program. CES data are computed from samples of businesses drawn from the ES-202 universe. The sample in any given month is quite large, currently including around 400,000 worksites employing around a third of all nonfarm payroll workers in the nation, but nevertheless, the data are contaminated with sampling errors. For most industries, BEA receives monthly not-seasonally adjusted CES data on employment, averages the monthly data to quarterly frequency, seasonally adjusts, then uses the growth rate of this number from the previous quarter as an extrapolator for the idiosyncratic state level variation in wages and salary income for that industry.[2] The base for the extrapolation is the level from the prior quarter computed from ES-202 data, aggregating across industries produces $\Delta \mathrm{WS}^p_{i,t} = \frac{\mathrm{WS}^p_{i,t} - \mathrm{WS}^s_{i,t-1}}{\mathrm{WS}^s_{i,t-1}}$.

We examine several measures of the size of revisions to the state wage and salary growth rates, from the preliminary estimates to the latest available numbers. Two are mean squared total revisions (MSTR), and mean absolute total revisions (MATR):

$$MSTR = \frac{1}{IT} \sum_t \sum_i \left(\Delta \mathrm{WS}^l_{i,t} - \Delta \mathrm{WS}^p_{i,t} \right)^2, \tag{1}$$

and:

$$MATR = \frac{1}{IT} \sum_t \sum_i \left| \Delta \mathrm{WS}^l_{i,t} - \Delta \mathrm{WS}^p_{i,t} \right|. \tag{2}$$

Here I is the number of states, and T is the number of periods we are considering. These are useful measures, and we will examine them. But they give equal weight to states of vastly different sizes; we may want to weight the revisions to California's growth rates more heavily than Vermont's. For weights, we start with the base for $\Delta \mathrm{WS}^p_{i,t}$, namely the second estimate of that state's wage and salary income lagged one period, $\mathrm{WS}^s_{i,t-1}$; we then normalize these weights so they sum over states to unity in each period,[3] so $w_{i,t} = \frac{\mathrm{WS}^s_{i,t-1}}{\sum_i \mathrm{WS}^s_{i,t-1}}$. Then weighted mean squared total revisions (WMSTR), and weighted mean absolute total revisions (WMATR) are:

$$WMSTR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left(\Delta \mathrm{WS}^l_{i,t} - \Delta \mathrm{WS}^p_{i,t} \right)^2, \tag{3}$$

and:

$$WMATR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left| \Delta \mathrm{WS}^l_{i,t} - \Delta \mathrm{WS}^p_{i,t} \right|. \tag{4}$$

The primary goal of the paper is to reduce (3) and (4) by replacing $\Delta\text{WS}^p_{i,t}$ with a better estimate of $\Delta\text{WS}^l_{i,t}$, some new estimate that we'll call $\Delta\widehat{\text{WS}}^l_{i,t}$.

Each state level growth rate computed by BEA is the sum of an aggregate component and a state-specific, idiosyncratic component. Call the aggregate component of each preliminary growth rate $\Delta\text{WS}^p_{a,t} = \sum_i w_{i,t}\text{WS}^p_{i,t}$, and the idiosyncratic component for each state $\Delta\text{WS}^p_{i-a,t} = \Delta\text{WS}^p_{i,t} - \Delta\text{WS}^p_{a,t}$ (the difference between the state growth rate and the national growth rate). For the idiosyncatic growth rates, we then have:

$$\sum_i w_{i,t}\text{WS}^p_{i-a,t} = 0 \quad \forall t.$$

We can similarly decompose the latest available data $\Delta\text{WS}^l_{i,t}$. Substituting these decompositions into (3) and (4), we see that WMSTR and WMATR contain both revisions to both the aggregate component and idiosyncratic components of the growth rates:

$$WMSTR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left(\left(\Delta\text{WS}^l_{a,t} - \Delta\text{WS}^p_{a,t}\right) + \left(\Delta\text{WS}^l_{i-a,t} - \Delta\text{WS}^p_{i-a,t}\right) \right)^2,$$

and:

$$WMATR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left| \left(\Delta\text{WS}^l_{a,t} - \Delta\text{WS}^p_{a,t}\right) + \left(\Delta\text{WS}^l_{i-a,t} - \Delta\text{WS}^p_{i-a,t}\right) \right|.$$

BEA adjusts the aggregate component $\Delta\text{WS}^p_{a,t}$ of the preliminary state growth rates to equal the currently prevailing national wage and salary growth rate, net of some minor adjustments. The currently prevailing national growth rate is computed using data and methods quite different from the state-level growth rates; in this paper we leave $\Delta\text{WS}^p_{a,t}$ unaltered, examining strategies that modify only the idiosyncratic variation $\Delta\text{WS}^p_{i-a,t}$. We modify these idiosyncratic growth rates, replacing them with new $\Delta\widehat{\text{WS}}^l_{i-a,t}$ designed to minimize weighted mean squared idiosyncratic revisions (WMSIR), and weighted mean absolute idiosyncratic revisions (WMAIR):[4]

$$(5) \qquad WMSIR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left(\Delta \mathrm{WS}^l_{i-a,t} - \Delta \widehat{\mathrm{WS}^l_{i-a,t}} \right)^2,$$

and:

$$(6) \qquad WMAIR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left| \Delta \mathrm{WS}^l_{i-a,t} - \Delta \widehat{\mathrm{WS}^l_{i-a,t}} \right|.$$

Given the practice of controlling to the national growth rates, we must ensure that our new preliminary idiosyncratic estimates sum to zero in each period:

$$(7) \qquad \sum_i w_{i,t} \Delta \widehat{\mathrm{WS}^l_{i-a,t}} = 0 \quad \forall t.$$

In this paper, we consider only $\Delta \widehat{\mathrm{WS}^l_{i-a,t}}$ that satisfy this property. In other words, we consider solutions to the problem of minimizing (5) or (6) subject to (7) holding true.

Summary statistics on the variability of the idiosyncratic growth rates - means of their squared values (approximately equal to their variances) and means of their absolute values - are reported in table 1. Data cover the 50 states plus the District of Columbia, and extend from 1980Q1-2001Q4 (4488 total observations); the table reports variability measures for this full sample, as well as the 1996Q1-2001Q4 sub-sample that will be used later for out-of-sample evaluation. Panels A and B report results where different states' growths rate are weighted by $w_{i,t}$; panels C and D report results where states' growth rates are unweighted. In general, the weighted variances and absolute values are less than the unweighted, indicating that the growth rate of wage and salary income is more volatile in small states than in large states.For both the weighted and unweighted statistics, the variability of $\Delta \mathrm{WS}^p_{i-a,t}$ is considerably less than the variability of $\Delta \mathrm{WS}^l_{i-a,t}$. Given BEA methodology, such a result is not obvious a priori - arguing for it is the fact that $\Delta \mathrm{WS}^{l}_{i-a,t}$ includes variation from earnings per worker as well as total employment, while $\Delta \mathrm{WS}^{p}_{i-a,t}$ includes only variation from total employment; arguing against it is the fact that $\Delta \mathrm{WS}^{p}_{i-a,t}$ includes variability from sampling errors while $\Delta \mathrm{WS}^{l}_{i-a,t}$ does not.[5] Another interesting fact to note is the decline in variability of CES growth rates $\Delta \mathrm{WS}^{p}_{i-a,t}$ in the 1996-2001 sub-sample, especially in the unweighted statistics; the variability of the growth rates computed from UI data does not fall by nearly as much if at all.

Finally, table 1 reports weighted and unweighted mean squared and mean absolute values of $\Delta \mathrm{WS}^{l}_{i-a,t} - \Delta \mathrm{WS}^{p}_{i-a,t}$, or WMSIR, WMAIR, MSIR, and MAIR. For the full sample each these quantities is smaller than its counterpart for $\Delta \mathrm{WS}^{l}_{i-a,t}$ alone, the weighted and unweighted mean squared and mean absolute values of $\Delta \mathrm{WS}^{l}_{i-a,t}$. However for the 1996-2001 sub-sample this is not the case, indicating that over this sub-sample mean absolute and squared idiosyncratic revisions would have been smaller had BEA set to zero the idiosycratic component of the state-level preliminary estimates. This points to some limitations to the current BEA practice of extrapolation.

II. Re-Scaling the Preliminary Estimates: Homogeneous β_t

The extrapolation procedure assumes a one-for-one relationship between $\Delta \mathrm{WS}^{l}_{i-a,t}$ and $\Delta \mathrm{WS}^{p}_{i-a,t}$, setting $\Delta \widehat{\mathrm{WS}^{l}}_{i-a,t} = \Delta \mathrm{WS}^{p}_{i-a,t}$. A more general estimate would be:

$$\Delta \widehat{\mathrm{WS}^{l}}_{i-a,t} = \beta_t \Delta \mathrm{WS}^{p}_{i-a,t},$$

where the β_t do not necessarily equal to 1. This is the essence of the basic efficiency test considered in this paper: will the preliminary estimates become better predictors of later estimates if they are re-scaled somehow; in the section we allow (limited) variation in β_t over time but no variation across states. It is immediately clear that an estimate of this form will satisfy (7), as:

$$\sum_i w_{i,t}\beta_t \Delta \mathrm{WS}^p_{i-a,t} = \beta_t \sum_i w_{i,t} \Delta \mathrm{WS}^p_{i-a,t} = 0.$$

We have at least two good reasons to suppose $\beta_t \neq 1$. First, the CES data used to compute $\Delta\mathrm{WS}^p_{i-a,t}$ are contaminated by sampling errors. These bias β_t towards zero, so even if the relation between $\Delta\mathrm{WS}^l_{i-a,t}$ and $\Delta\mathrm{WS}^p_{i-a,t}$ net of sampling errors were in fact one-for-one, the relation between $\Delta\mathrm{WS}^l_{i-a,t}$ and $\Delta\mathrm{WS}^p_{i-a,t}$ inclusive of sampling errors would be less than one-for-one. Second, the CES data do not capture much of the variation in $\Delta\mathrm{WS}^l_{i-a,t}$ from earnings per worker; unfortunately the effect of this omitted variation on β_t is less clear than the effect of sampling errors.

With $\Delta\widehat{\mathrm{WS}^l_{i-a,t}} = \beta_t \Delta\mathrm{WS}^p_{i-a,t}$, we may use weighted ordinary least squares (OLS) regression to minimize (5) by choice of β_t, and weighted median (least absolute deviations, or LAD) regression to minimize (6) by choice of β_t. The panel regressions are of the form:

$$\Delta\mathrm{WS}^l_{i-a,t} = \beta_t \Delta\mathrm{WS}^p_{i-a,t} + U_{i-a,t}. \tag{8}$$

We attempt to identify strategies for estimating $\Delta\widehat{\mathrm{WS}^l_{i-a,t}}$ that can be implemented by BEA in real time, and show that had these strategies been implemented, WMSIR and WMAIR would have been smaller. As such, we follow an out-of-sample forecasting routine, with out-of-sample period starting in 1996Q1. For our first out-of-sample quarter, we imagine BEA in July 1996 (four months after the close of the quarter), estimating (8) on data from 1980Q1 up until some cut-off quarter, and using the estimated $\widehat{\beta}_t$ to produce the 51 predicted values $\widehat{\beta}_t \Delta\mathrm{WS}^p_{i-a,t}$ for 1996Q1. The choice of cutoff quater raises a couple of issues. First, the data available to BEA for 1995Q4 and the prior couple of quaters at that time would be in second vintage form, $\Delta\mathrm{WS}^s_{i-a,t}$. As table 1 shows, the variance of the second vintage estimates is substantially larger than the variance of the latest available estimates, probably because the seasonal adjustment procedure, which uses future quarters as well as lagged quarters to estimate seasonal factors, is incomplete at this point. Given the dissimilarity of the second vintage estimates to the latest available estimates, using these latest quarters in second vintage form may bias the estimates of β_t designed to minimize (5) and (6). The second issue with our choice of cutoff quarter has to do with limitations of the data employed in this paper: clearly the latest available, 2005 vintage data used in this paper, for all quarters, would not have been available to BEA in July 1996. For both these reasons, we chose the cutoff quarter for our in-sample period to be three years prior to the quarter to be forecasted; so for our $\widehat{\beta}_t \Delta \mathrm{WS}^p_{i-a,t}$ estimates for 1996Q1, we use $\widehat{\beta}_t$ estimated from (8) using data from 1980Q1 to 1993Q1. Our working assumption is that the 1980Q1-1993Q1 data available to BEA in July 1996 is similar enough to the 1980Q1-1993Q1 data available to BEA in March 2005 that our estimates of $\widehat{\beta}_t$ are largely unaffected by this substitution.[6]

Having produced the 51 predicted values $\Delta \widehat{\mathrm{WS}}^l_{i-a,t}$ for 1996Q1, the in-sample period is then extended forward one quarter to re-estimate the regression parameters, which are used to produce the 51 predicted values for 1996Q2; this rolling regression procedure continues through 2001Q4, producing 24 predicted values for each state, 1224 in total. Given these predicted values, we compute idiosyncratic revisions, and compare them to actual idiosyncratic revisions that prevailed under the extrapolation procedure with $\Delta \widehat{\mathrm{WS}}^l_{i-a,t} = \Delta \mathrm{WS}^p_{i-a,t}$. We will use our various idiosyncratic revision measures (WMSIR, MSIR, WMAIR, MAIR) to compare the old revisions with the hypothetical new ones.

The first row of table 2 shows the revision measures for the current extrapolation procedure, which we call $WMAIR_c$, $WMSIR_c$, $MAIR_c$, and $MSIR_c$. The second row shows results from ordinary least squares estimation of (8). For the 24 in-sample regressions, $\widehat{\beta}_t$ ranged from 0.63 to 0.61, falling over the sample period, each with a standard error of about 0.06; we can clearly reject the hypthothesis that $\beta_t = 1$. These standard errors are computing using variances that are robust to arbitrary heteroskedasticity, autocorrelation up to eighth-order, and contemporaneous correlation between states; it's computation is described in Appendix A.[7] The lines in the row report $WMAIR$, $WMSIR$, $MAIR$, and $MSIR$, and the ratio of each of these measures with its counterpart for the current extrapolation procedure. Absolute revisions fall by about 5-6% compared to the old procedure, $WMSIR$ falls by 6%, and $MSIR$ falls by 10%. The difference between the weighted and unweighted measures indicates that greater reductions in revisions may be achieved for small states than for large states. The last number in the row (labelled $t_{\Delta \mathrm{WMAIR}}$) is a t-statistic measuring the statistical significance of the difference between $WMAIR$ and $WMAIR_c$ from the current procedure. This t-statistic is computed following the asymptotic formulas recommended in Diebold and Mariano (1995) generalized to a panel context; the variance of ΔWMAIR is computed in a robust fashion similar to the OLS standard errrors, allowing for autocorrelation and contemporaneous cross-state correlation of arbitrary form, with details provided in Appendix B. With a value of about 5, this t-statistic strongly rejects at conventional significance levels the hypothesis that the fall in $WMAIR$ obtained from scaling down β_t is equal to zero.

The third row in the table reports results from least absolute deviations (LAD) estimation of (8); these $\widehat{\beta_t}$ ranged from about 0.59 to 0.58, somewhat smaller than their OLS counterparts. Comparing the OLS and LAD estimates further, Figure 1 shows sub-sample OLS and LAD estimates for each of the 22 years in the full sample; each sub-sample contains 204 observations. As can be seen, the LAD βs are somewhat more stable across the sample, and for this reason perhaps more trustworthy. In any event, the size of the reductions in $WMAIR$, $WMSIR$, $MAIR$, and $MSIR$ are quite similar whether we use LAD or OLS; under either set of β_t we reject the hypothesis that the fall in $WMAIR$ is equal to zero. Using the LAD β_t, table 3A shows the ratios $\frac{WMSIR}{WMSIR_c}$ and $\frac{WMAIR}{WMAIR_c}$ broken down by quarter. For most quarters, weighted mean and absolute revisions fall using these β_t instead of imposing $\beta_t = 1$. The $\frac{WMSIR}{WMSIR_c}$ in 1999 are a bit of a problem, as we could have guessed given Figure 1.

The state-by-state breakdown of these reductions in WMSIR and WMAIR is of considerable interest as well; these are reported for the LAD β_t in table 3B, with states sorted by a a measure of size. Both WMSIR falls relative to extrapolation for 37 out of the 51 states in the panel and WMAIR falls for 39 out of the 51 states. Over the short out-of-sample period we have here, only 24 quarters for each state, we should expect some states to fail to exhibit improvements simply due to chance, even when asymptotically, improvements exist for all states; simulations confirm that we should expect about this many failures even if the homogeneous β_t model is true.[8] However it is certainly of note that each of the largest three states - California, New York, and Texas - fails to exhibit forecast improvements, each deteriorating in fact when we examine $\frac{WMSIR}{WMSIR_c}$.

III. Re-Scaling the Preliminary Estimates: Heterogeneous $\beta_{i,t}$

We next explore whether further reductions in revisions may be acheived by allowing the scaling factors to vary across states. The state specific scaling factors would be $\beta_{i,t}$, with $\Delta\widehat{\mathrm{WS}}^l_{i-a,t} = \beta_{i,t}\Delta\mathrm{WS}^p_{i-a,t}$; however a complication arises here, as condition (7) will in general not be met:

$$\sum_i w_{i,t}\beta_{i,t}\Delta\mathrm{WS}^p_{i-a,t} \neq 0.$$

While this sum may be close to zero in most periods,[9] it is better to impose a correction ensuring condition (7) holds. We can do this if we take:

$$\Delta\widehat{\mathrm{WS}}^l_{i-a,t} = \beta_{i,t}\Delta\mathrm{WS}^p_{i-a,t} - \sum_j w_{j,t}\beta_{j,t}\Delta\mathrm{WS}^p_{j-a,t}. \quad (9)$$

It can be readily verified that (7) is met for this $\Delta\widehat{\mathrm{WS}}^{l}_{i-a,t}$. As a practical matter, it should be noted that these $\Delta\widehat{\mathrm{WS}}^{l}_{i-a,t}$ could be computed using $\beta_{i,t}\Delta\mathrm{WS}^{p}_{i-a,t}$ alone as long as we control to the national growth rate after computing those estimates, as controlling to national will serve to subtract $\sum_j w_{j,t}\beta_{j,t}\Delta\mathrm{WS}^{p}_{j-a,t}$ from each state time series and in the end give us (9). In some cases it may be simpler for an analyst to compute $\Delta\widehat{\mathrm{WS}}^{l}_{i-a,t}$ in this way.

For purposes of estimation, when minimizing (5) or (6), we minimize:

$$\frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left(\Delta\mathrm{WS}^{l}_{i-a,t} - \left(\beta_{i,t}\Delta\mathrm{WS}^{p}_{i-a,t} - \sum_j w_{j,t}\beta_{j,t}\Delta\mathrm{WS}^{p}_{j-a,t} \right) \right)^2, \quad \text{or:}$$

$$\frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left| \Delta\mathrm{WS}^{l}_{i-a,t} - \left(\beta_{i,t}\Delta\mathrm{WS}^{p}_{i-a,t} - \textstyle\sum_j w_{j,t}\beta_{j,t}\Delta\mathrm{WS}^{p}_{j-a,t} \right) \right|$$

by choice of $\beta_{i,t}$. These problems may again be solved by simple OLS and LAD regression, with explanatory variables appropriately defined. For each state k write $\Delta\mathrm{WS}^{p}_{k-a,t}$ and $\Delta\mathrm{WS}^{l}_{k-a,t}$ in vector form, so:

$$\Delta\mathrm{WS}^{p}_{k-a} = \begin{pmatrix} \Delta\mathrm{WS}^{p}_{k-a,1} \\ \Delta\mathrm{WS}^{p}_{k-a,2} \\ \vdots \\ \Delta\mathrm{WS}^{p}_{k-a,T} \end{pmatrix}; \quad \Delta\mathrm{WS}^{l}_{k-a} = \begin{pmatrix} \Delta\mathrm{WS}^{l}_{k-a,1} \\ \Delta\mathrm{WS}^{l}_{k-a,2} \\ \vdots \\ \Delta\mathrm{WS}^{l}_{k-a,T} \end{pmatrix},$$

and further stacking the individual states together into a panel, our (unweighted) regression may be written as:

$$
\begin{bmatrix} \Delta\mathrm{WS}^{l}_{1-a} \\ \cdots\cdots \\ \Delta\mathrm{WS}^{l}_{2-a} \\ \cdots\cdots \\ \vdots \\ \cdots\cdots \\ \Delta\mathrm{WS}^{l}_{I-a} \end{bmatrix} = \beta_1 \left(\begin{bmatrix} \Delta\mathrm{WS}^{p}_{1-a} \\ \cdots\cdots \\ 0 \\ \cdots\cdots \\ \vdots \\ \cdots\cdots \\ 0 \end{bmatrix} - \begin{bmatrix} \Delta\mathrm{WS}^{p}_{1-a} \\ \cdots\cdots \\ \Delta\mathrm{WS}^{p}_{1-a} \\ \cdots\cdots \\ \vdots \\ \cdots\cdots \\ \Delta\mathrm{WS}^{p}_{1-a} \end{bmatrix}_W \right) + \cdots
$$

$$
\cdots + \beta_I \left(\begin{bmatrix} 0 \\ \cdots\cdots \\ 0 \\ \cdots\cdots \\ \vdots \\ \cdots\cdots \\ \Delta\mathrm{WS}^{p}_{I-a} \end{bmatrix} - \begin{bmatrix} \Delta\mathrm{WS}^{p}_{I-a} \\ \cdots\cdots \\ \Delta\mathrm{WS}^{p}_{I-a} \\ \cdots\cdots \\ \vdots \\ \cdots\cdots \\ \Delta\mathrm{WS}^{p}_{I-a} \end{bmatrix}_W \right) + \begin{bmatrix} u_{1-a} \\ \cdots \\ u_{2-a} \\ \cdots \\ \vdots \\ \cdots \\ u_{I-a} \end{bmatrix},
$$

where the elements of vectors with the W subscript have been multiplied by their respective weights, the zeros in this expression represent vectors of length T, and u_{k-a} represents the vector of errors for state k. Estimating this regression by weighted least squares minimizes (5), and estimating it by weighted least absolute deviations minimizes (6). We follow the same rolling regression and out-of-sample evaluation procedure as in the previous section; table 4 reports the main summary statistics from this analysis.

Once again the results obtained from OLS estimation are quite similar to those obtained from LAD. Allowing for heterogeneity in the scaling factors leads to some incremental improvements compared with the homogeneous scaling factor results; weighted and unweighted absolute revisions still fall by about 6% compared to the old procedure, but $WMSIR$ now falls by 10%, and $MSIR$ falls by 13%. We again strongly reject the hypothesis that the fall in $WMAIR$ equals zero. Table 5A shows $\frac{WMSIR}{WMSIR_c}$ and $\frac{WMAIR}{WMAIR_{extrap}}$ broken down by quarter for the OLS $\beta_{i,t}$, and table 6A shows that breakdown for the LAD $\beta_{i,t}$. The biggest problem year with the β_t estimates, 1999, is now longer much of an issue. Tables 5B and 6B show the $\frac{WMSIR}{WMSIR_c}$ and $\frac{WMAIR}{WMAIR_c}$ for each state, along with the range of $\beta_{i,t}$ from the 24 in-sample estimates, and the standard errors for the OLS estimates, again computed using robust variance-covariance matrices as in Appendix A. For the individual states, the $\beta_{i,t}$ vary much more as we roll the sample forward than does the aggregate β_t; random fluctuations in effectively much smaller samples are surely to blame for part of this. However the improvements in the out-of-sample revisions argue that there is indeed substantial heterogeneity in the scaling factors across states; the $\beta_{i,t}$ for Texas and New York are evidently larger than average, and accounting for this alleviates the deterioration in $\frac{WMSIR}{WMSIR_c}$ we see in the homogeneous β_t model.

IV. Conclusion and Extensions

This paper has demonstrated how basic efficiency tests may be conducted on idiosyncratic variation in a panel of preliminary estimates or predictions, implementing the tests on BEA's preliminary estimates of state wage and salary growth. We show how to exploit the tests to develop simple strategies for improving the preliminary estimates, demonstrating with an out-of-sample analysis that revisions to BEA's preliminary numbers would have been significantly smaller had the strategies been implemented. BEA could implement these simple strategies without changing current procedure much at all. Since controlling to the national estimate is generally the last step in the process of computing the preliminary state growth rates, BEA need not even compute the idiosyncratic state-level variation in the estimates; all it need do is re-scale the preliminary numbers by a factor of around 0.6, or by some set of state-specific factors, as the penultimate step in the process before controlling to the national total. BEA is currently evaluating the feasibility of implementing such re-scalings.

Appendix A: Standard Errors for the Weighted Least Squares Estimator

Let IT denote the total sample size; let $\mathbf{X}$ denote the $IT \times K$ matrix of regressors; let $\boldsymbol{\Omega}$ represent the $IT \times IT$ variance-covariance matrix of regression residuals; finally let $\mathbf{W}$ denote the $IT \times IT$ diagonal matrix with the vector of the square root of the weights on the diagonal. Then, following standard practice, the variance-covariance matrix of the OLS parameter estimates is computed as:

$$(\mathbf{X'WX})^{-\mathbf{1}}\mathbf{X'W\Omega WX}(\mathbf{X'WX})^{-\mathbf{1}}.$$

$\mathbf{X'W\Omega WX}$ is the sum of two additive components. The first component (which we shall call $\mathbf{X'W\Omega_0 WX}$) is robust to both arbitrary heteroskedasticity and cross correlation. The matrix can be represented as:

$$\mathbf{X'W\Omega_0 WX} = \sum_{i=1}^{I}\sum_{j=1}^{I}\sum_{t=1}^{T}(x'_{i,t}\sqrt{w_{i,t}}u_{i,t}u_{j,t}\sqrt{w_{j,t}}x_{j,t} + x'_{j,t}\sqrt{w_{j,t}}u_{j,t}u_{i,t}\sqrt{w_{i,t}}x_{i,t}),$$

where $x_{i,t}$ corresponds to the appropriate row vector of $\mathbf{X}$. Rearranging summations yields the convenient expression for computing this matrix used in this paper:

$$\begin{aligned}\mathbf{X'W\Omega_0 WX} &= \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{I}(x'_{i,t}\sqrt{w_{i,t}}u_{i,t}u_{j,t}\sqrt{w_{j,t}}x_{j,t} + x'_{j,t}\sqrt{w_{j,t}}u_{j,t}u_{i,t}\sqrt{w_{i,t}}x_{i,t}) \\ &= \sum_{t=1}^{T}\mathbf{X'_t W_t \Omega_{0,t} W_t X_t}.\end{aligned}$$

Here $\mathbf{X_t}$ denotes the I rows of $\mathbf{X}$ that correspond to the year t cross sectional observations. Similarly, $\mathbf{\Omega_{0,t}}$ denotes the matrix $\mathbf{u_t u'_t}$, the outer product of the vector of time t regression residuals, and $\mathbf{W_t}$ denotes the diagonal matrix with the square root of the weights for time the t observations. The last expression makes clear that, after sorting the data by year, the cross-correlation corrected variance-covariance matrix of residuals will be block diagonal (ignoring any autocorrelation for the moment), with each each block corresponding to a year. This variance-covariance matrix has the same form as those used in clustered samples to correct for arbitrary within-cluster correlations, the only difference being that each year plays the role of a cluster.

A second component of the estimated matrix $\mathbf{X'W\Omega WX}$ corrects for autocorrelation as suggested by Whitney K. Newey and Kenneth D. West (1987):

$$\mathbf{X'W\Omega_k WX} = \sum_{k=1}^{k'} \left(\frac{k'+1-k}{k'+1} \right) \sum_{j=1}^{I} \sum_{t=1+k}^{T} \begin{pmatrix} x'_{j,t}\sqrt{w_{j,t}}u_{j,t}u_{j,t-k}\sqrt{w_{j,t-k}}x_{j,t-k} \\ +x'_{j,t-k}\sqrt{w_{j,t-k}}u_{j,t-k}u_{j,t}\sqrt{w_{j,t}}x_{j,t} \end{pmatrix}.$$

In this paper k' is set to eight, so the matrix corrects for eighth-order autocorrelation. The full $\mathbf{X'W\Omega WX}$ is then computed as:

$$\mathbf{X'W\Omega WX} = \mathbf{X'W\Omega_0 WX} + \mathbf{X'W\Omega_k WX}.$$

Appendix B: Standard Error for the Difference between Two Sets of Panel Forecasts

Given the two forecasts for state i in period t, call the difference between their loss functions $d_{i,t}$; Diebold and Mariano (1995) call this the loss-differential series. When the loss function is measured as the absolute value of the forecast error, we have:

$$d_{i,t} = \left| \Delta \mathrm{WS}^{l}_{i-a,t} - \Delta \widehat{\mathrm{WS}^{l}_{i-a,t}} \right| - \left| \Delta \mathrm{WS}^{l}_{i-a,t} - \Delta \mathrm{WS}^{p}_{i-a,t} \right|.$$

Then the weighted average of $d_{i,t}$ is the difference between old WMAIR and new WMAIR, or ΔWMAIR; this is the sample mean loss-differential: $\overline{d} = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} d_{i,t}$. The variance of $\overline{d}$ allows for arbitrary heteroskedasticity in the loss-differential series, correlation between the loss-differentials for different states in any given time period (contemporaneous cross correlation in the loss-differentials), and eighth-order autocorrelation in the loss-differentials. With $k' = 8$, it is computed as:

$$
\begin{aligned}
V\left(\overline{d}\right) \quad = \quad & \frac{1}{\sum_t \sum_j w_{j,t}} \sum_{i=1}^{I} \sum_{j=1}^{I} \sum_{t=1}^{T} \left(\begin{array}{c} \sqrt{w_{i,t}} \left(d_{i,t} - \overline{d}\right) \left(d_{j,t} - \overline{d}\right) \sqrt{w_{j,t}} \\ +\sqrt{w_{j,t}} \left(d_{j,t} - \overline{d}\right) \left(d_{i,t} - \overline{d}\right) \sqrt{w_{i,t}} \end{array} \right) \\
& + \frac{1}{\sum_t \sum_j w_{j,t}} \sum_{k=1}^{k'} \sum_{j=1}^{I} \sum_{t=1+k}^{T} \left(\begin{array}{c} \sqrt{w_{j,t}} \left(d_{j,t} - \overline{d}\right) \left(d_{j,t-k} - \overline{d}\right) \sqrt{w_{j,t-k}} \\ +\sqrt{w_{j,t-k}} \left(d_{j,t-k} - \overline{d}\right) \left(d_{j,t} - \overline{d}\right) \sqrt{w_{j,t}}. \end{array} \right).
\end{aligned}
$$

The set of terms in the first line of this expression is computed using the same set of rearrangements used to compute $\mathbf{X'W\Omega_0WX}$ in Appendix A.

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Table 1: Summary Statistics
BEA Estimates of State Wage and Salary Growth, Idiosyncratic Variation

Panel A: Weighted Mean of Squared Values

	$\Delta\mathrm{WS}^p_{i-a,t}$	$\Delta\mathrm{WS}^s_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t} - \Delta\mathrm{WS}^p_{i-a,t}$
1980-2001	0.53	1.19	0.98	0.87
1996-2001	0.29	1.34	1.09	1.10

Panel B: Weighted Mean of Absolute Values

	$\Delta\mathrm{WS}^p_{i-a,t}$	$\Delta\mathrm{WS}^s_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t} - \Delta\mathrm{WS}^p_{i-a,t}$
1980-2001	0.50	0.80	0.70	0.68
1996-2001	0.40	0.87	0.73	0.73

Panel C: Unweighted Mean of Squared Values

	$\Delta\mathrm{WS}^p_{i-a,t}$	$\Delta\mathrm{WS}^s_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t} - \Delta\mathrm{WS}^p_{i-a,t}$
1980-2001	0.80	1.55	1.23	1.11
1996-2001	0.42	1.53	1.13	1.20

Panel D: Unweighted Mean of Absolute Values

	$\Delta\mathrm{WS}^p_{i-a,t}$	$\Delta\mathrm{WS}^s_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t}$	$\Delta\mathrm{WS}^l_{i-a,t} - \Delta\mathrm{WS}^p_{i-a,t}$
1980-2001	0.62	0.92	0.79	0.78
1996-2001	0.47	0.94	0.78	0.80

Table 2: Measures of Size of Revisions, 1996-2001 Out-of-Sample Period

Baseline, Current Procedure

$WMAIR_c$	$WMSIR_c$	$MAIR_c$	$MSIR_c$
0.734	**1.097**	**0.801**	**1.204**

OLS Estimates of $\widehat{\beta}_t$
$\widehat{\beta}_t$ ranges from 0.61-0.63 (0.06) standard error

WMAIR	$\frac{WMAIR}{WMAIR_c}$	WMSIR	$\frac{WMSIR}{WMSIR_c}$	MAIR	$\frac{MAIR}{MAIR_c}$	MSIR	$\frac{MSIR}{MSIR_c}$	$t_{\Delta \text{WMAIR}}$
0.701	0.95	**1.027**	0.94	**0.757**	0.94	**1.079**	0.90	5.16

LAD Estimates of $\widehat{\beta}_t$
$\widehat{\beta}_t$ ranges from 0.58-0.59

WMAIR	$\frac{WMAIR}{WMAIR_c}$	WMSIR	$\frac{WMSIR}{WMSIR_c}$	MAIR	$\frac{MAIR}{MAIR_c}$	MSIR	$\frac{MSIR}{MSIR_c}$	$t_{\Delta \text{WMAIR}}$
0.700	0.95	**1.025**	0.93	**0.755**	0.94	**1.072**	0.89	4.93

Table 3A: Out-of-Sample Revision Measures by Quarter, Relative to Current β_t homogeneous across states, LAD

Quarter	$\frac{WMSIR}{WMSIR_c}$	$\frac{WMAIR}{WMAIR_c}$
9601	0.77	0.91
9602	1.01	0.90
9603	0.76	0.89
9604	0.90	0.96
9701	0.82	0.88
9702	0.93	1.04
9703	0.86	0.95
9704	0.69	0.85
9801	0.81	0.92
9802	0.80	0.84
9803	1.00	0.99
9804	0.91	0.96
9901	1.00	0.96
9902	1.13	1.05
9903	1.00	1.01
9904	0.96	0.97
10001	0.93	0.94
10002	0.95	0.97
10003	1.02	1.00
10004	0.98	1.00
10101	0.88	0.92
10102	0.93	0.95
10103	0.87	0.95
10104	1.03	1.01

Table 3B: Out-of-Sample Revision Measures by State, Relative to Current β_t homogeneous across states, LAD

State	$\frac{WMSIR}{WMSIR_c}$	$\frac{WMAIR}{WMAIR_c}$
Wyoming	0.88	0.89
Vermont	0.76	0.89
North Dakota	0.98	1.02
South Dakota	1.08	1.07
Montana	0.85	0.89
Alaska	1.01	1.00
Idaho	0.67	0.85
Delaware	0.70	0.83
Rhode Island	0.85	0.90
Maine	1.01	0.99
New Hampshire	0.84	0.94
Hawaii	1.16	1.12
New Mexico	1.00	1.01
West Virginia	0.86	0.91
Nebraska	1.04	1.10
Nevada	0.90	0.97
Utah	0.84	0.97
Arkansas	0.72	0.91
Mississippi	0.91	0.88
DC	0.97	0.94
Kansas	1.15	1.07
Iowa	0.87	0.86
Oklahoma	0.84	0.93
Oregon	0.80	0.93
Kentucky	0.85	0.93
South Carolina	0.80	0.89
Alabama	0.92	0.95
Louisiana	1.07	0.99
Arizona	1.17	1.08
Colorado	0.94	0.95
Connecticut	0.74	0.87
Tennessee	0.83	0.92
Wisconsin	1.01	0.94
Minnesota	0.95	1.04
Missouri	0.82	0.91
Maryland	0.85	0.96
Indiana	0.77	0.87
Washington	0.86	0.93

North Carolina	0.74	0.87
Virginia	0.93	0.98
Georgia	0.69	0.81
Massachusetts	0.82	0.95
New Jersey	1.09	1.00
Michigan	0.78	0.88
Ohio	0.97	0.93
Pennsylvania	0.81	0.91
Florida	0.66	0.79
Illinois	0.78	0.86
Texas	1.11	0.99
New York	1.07	1.04
California	1.03	0.99

Table 4: Measures of Size of Revisions, 1996-2001 Out-of-Sample Period

Baseline, Current Procedure

$WMAIR_c$	$WMSIR_c$	$MAIR_c$	$MSIR_c$
0.734	**1.097**	**0.801**	**1.204**

OLS Estimates of $\widehat{\beta_{i,t}}$

WMAIR	$\frac{WMAIR}{WMAIR_c}$	WMSIR	$\frac{WMSIR}{WMSIR_c}$	MAIR	$\frac{MAIR}{MAIR_c}$	MSIR	$\frac{MSIR}{MSIR_c}$	$t_{\Delta\text{WMAIR}}$
0.693	0.94	**0.990**	0.90	**0.749**	0.94	**1.046**	0.87	4.53

LAD Estimates of $\widehat{\beta_{i,t}}$

WMAIR	$\frac{WMAIR}{WMAIR_c}$	WMSIR	$\frac{WMSIR}{WMSIR_c}$	MAIR	$\frac{MAIR}{MAIR_c}$	MSIR	$\frac{MSIR}{MSIR_c}$	$t_{\Delta\text{WMAIR}}$
0.693	0.94	**0.987**	0.90	**0.750**	0.94	**1.049**	0.87	4.88

Table 5A: Out-of-Sample Revision Measures by Quarter, Relative to Current $\beta_{i,t}$ heterogeneous across states, OLS

Quarter	$\frac{WMSIR}{WMSIR_c}$	$\frac{WMAIR}{WMAIR_c}$
9601	0.89	1.00
9602	0.94	0.79
9603	0.68	0.85
9604	0.91	0.96
9701	0.76	0.84
9702	0.90	1.04
9703	0.85	0.98
9704	0.65	0.83
9801	0.75	0.88
9802	0.76	0.81
9803	1.02	1.01
9804	0.98	0.99
9901	0.92	0.94
9902	0.96	0.97
9903	1.00	1.02
9904	0.84	0.94
10001	0.85	0.91
10002	0.94	0.97
10003	1.07	1.02
10004	0.97	1.02
10101	0.97	0.92
10102	0.93	0.96
10103	0.85	0.95
10104	1.06	1.02

Table 5B: Out-of-Sample Revision Measures by State, Relative to Current $\beta_{i,t}$ heterogeneous across states, OLS

State	β (range)	se_β (range)	$\frac{WMSIR}{WMSIR_c}$	$\frac{WMAIR}{WMAIR_c}$
Wyoming	0.71 to 0.73	(0.17 to 0.19)	0.90	0.90
Vermont	0.16 to 0.26	(0.12 to 0.13)	0.64	0.83
North Dakota	0.98 to 1.00	(0.12 to 0.13)	0.98	0.98
South Dakota	0.66 to 0.73	(0.18 to 0.20)	1.02	1.03
Montana	0.32 to 0.33	(0.15 to 0.17)	0.84	0.89
Alaska	0.84 to 0.85	(0.09 to 0.10)	0.98	0.99
Idaho	0.46 to 0.59	(0.15 to 0.18)	0.65	0.84
Delaware	0.08 to 0.13	(0.06 to 0.06)	0.54	0.70
Rhode Island	0.27 to 0.34	(0.15 to 0.18)	0.86	0.90
Maine	0.35 to 0.40	(0.12 to 0.14)	1.03	1.00
New Hampshire	0.44 to 0.51	(0.15 to 0.17)	0.82	0.92
Hawaii	0.78 to 1.01	(0.18 to 0.22)	1.04	1.04
New Mexico	0.78 to 0.95	(0.20 to 0.30)	1.01	1.01
West Virginia	1.02 to 1.05	(0.08 to 0.09)	1.01	1.01
Nebraska	0.39 to 0.43	(0.12 to 0.14)	1.09	1.14
Nevada	0.63 to 0.77	(0.11 to 0.13)	0.92	0.98
Utah	0.81 to 0.94	(0.08 to 0.16)	0.96	0.99
Arkansas	0.37 to 0.41	(0.10 to 0.13)	0.62	0.89
Mississippi	0.54 to 0.64	(0.18 to 0.23)	0.90	0.87
DC	0.55 to 0.74	(0.11 to 0.15)	1.00	0.97
Kansas	0.16 to 0.19	(0.12 to 0.15)	1.88	1.23
Iowa	0.68 to 0.72	(0.16 to 0.17)	0.88	0.88
Oklahoma	1.03 to 1.13	(0.09 to 0.11)	1.04	1.02
Oregon	0.69 to 0.74	(0.13 to 0.16)	0.82	0.94
Kentucky	0.32 to 0.33	(0.09 to 0.09)	0.79	0.94
South Carolina	0.25 to 0.32	(0.13 to 0.15)	0.69	0.82
Alabama	0.40 to 0.46	(0.13 to 0.15)	0.90	0.95
Louisiana	0.97 to 1.16	(0.11 to 0.22)	0.99	0.99
Arizona	0.52 to 0.67	(0.15 to 0.18)	1.13	1.07
Colorado	0.89 to 1.05	(0.12 to 0.15)	0.99	0.99
Connecticut	0.42 to 0.46	(0.12 to 0.14)	0.68	0.82
Tennessee	0.03 to 0.11	(0.14 to 0.16)	0.68	0.87
Wisconsin	0.38 to 0.42	(0.16 to 0.18)	1.04	0.90
Minnesota	0.24 to 0.35	(0.13 to 0.14)	0.96	1.13
Missouri	-0.02 to 0.04	(0.10 to 0.11)	0.81	0.91
Maryland	0.27 to 0.36	(0.18 to 0.24)	0.82	0.96
Indiana	0.52 to 0.62	(0.14 to 0.15)	0.75	0.87
Washington	0.31 to 0.44	(0.15 to 0.21)	0.82	0.92

North Carolina	0.37 to 0.43	(0.10 to 0.11)	0.65	0.83
Virginia	0.53 to 0.57	(0.20 to 0.22)	0.94	0.99
Georgia	0.40 to 0.50	(0.12 to 0.14)	0.65	0.78
Massachusetts	0.30 to 0.34	(0.13 to 0.14)	0.74	0.94
New Jersey	0.28 to 0.38	(0.15 to 0.17)	1.20	1.02
Michigan	0.50 to 0.54	(0.09 to 0.10)	0.77	0.89
Ohio	0.46 to 0.50	(0.13 to 0.16)	0.95	0.92
Pennsylvania	0.36 to 0.39	(0.06 to 0.07)	0.74	0.88
Florida	0.46 to 0.51	(0.12 to 0.13)	0.63	0.81
Illinois	0.48 to 0.50	(0.10 to 0.11)	0.74	0.85
Texas	1.19 to 1.27	(0.17 to 0.18)	0.95	0.99
New York	1.07 to 1.16	(0.15 to 0.19)	1.00	1.00
California	0.32 to 0.49	(0.19 to 0.22)	1.04	0.99

Table 6A: Out-of-Sample Revision Measures by Quarter, Relative to Current $\beta_{i,t}$ heterogeneous across states, LAD

Quarter	$\frac{WMSIR}{WMSIR_c}$	$\frac{WMAIR}{WMAIR_c}$
9601	0.89	0.99
9602	0.94	0.79
9603	0.68	0.85
9604	0.91	0.97
9701	0.78	0.87
9702	0.89	1.03
9703	0.84	0.97
9704	0.67	0.85
9801	0.75	0.90
9802	0.75	0.83
9803	1.04	0.99
9804	1.00	1.00
9901	0.92	0.92
9902	0.93	0.96
9903	0.98	1.00
9904	0.80	0.93
10001	0.86	0.92
10002	0.93	0.95
10003	1.03	1.01
10004	0.97	1.02
10101	1.01	0.94
10102	0.95	0.97
10103	0.86	0.94
10104	1.09	1.04

Table 6B: Out-of-Sample Revision Measures by State, Relative to Current $\beta_{i,t}$ heterogeneous across states, LAD

State	β (range)	$\frac{WMSIR}{WMSIR_c}$	$\frac{WMAIR}{WMAIR_c}$
Wyoming	0.56 to 0.66	0.88	0.89
Vermont	0.12 to 0.15	0.62	0.82
North Dakota	1.16 to 1.21	1.03	1.00
South Dakota	0.62 to 0.76	1.01	1.03
Montana	0.18 to 0.19	0.87	0.89
Alaska	0.77 to 0.83	0.98	1.00
Idaho	0.58 to 0.60	0.68	0.86
Delaware	0.12 to 0.17	0.54	0.71
Rhode Island	0.16 to 0.25	0.87	0.90
Maine	0.31 to 0.38	1.04	1.01
New Hampshire	0.54 to 0.86	0.90	0.97
Hawaii	0.76 to 1.29	1.02	1.00
New Mexico	0.82 to 0.87	0.99	1.01
West Virginia	1.03 to 1.03	1.01	1.01
Nebraska	0.38 to 0.48	1.07	1.13
Nevada	0.54 to 0.66	0.91	0.98
Utah	0.78 to 0.96	0.98	1.00
Arkansas	0.40 to 0.58	0.66	0.89
Mississippi	0.36 to 0.66	0.90	0.86
DC	0.55 to 0.63	0.99	0.95
Kansas	0.24 to 0.27	1.66	1.16
Iowa	0.77 to 0.85	0.91	0.92
Oklahoma	1.02 to 1.05	1.02	1.01
Oregon	0.65 to 0.80	0.80	0.93
Kentucky	0.24 to 0.25	0.78	0.95
South Carolina	0.07 to 0.21	0.64	0.79
Alabama	0.32 to 0.37	0.89	0.95
Louisiana	1.02 to 1.16	0.98	0.99
Arizona	0.47 to 0.57	1.19	1.10
Colorado	0.87 to 1.14	1.01	1.01
Connecticut	0.51 to 0.62	0.72	0.86
Tennessee	0.00 to 0.15	0.69	0.87
Wisconsin	0.39 to 0.49	1.03	0.90
Minnesota	0.25 to 0.42	0.95	1.11
Missouri	-0.07 to 0.08	0.82	0.92
Maryland	0.18 to 0.31	0.81	0.95
Indiana	0.32 to 0.64	0.73	0.86
Washington	0.30 to 0.43	0.82	0.92

North Carolina	0.34 to 0.39	0.64	0.83
Virginia	0.53 to 0.59	0.95	1.00
Georgia	0.51 to 0.65	0.74	0.86
Massachusetts	0.47 to 0.48	0.78	0.94
New Jersey	0.34 to 0.43	1.20	1.03
Michigan	0.51 to 0.52	0.77	0.89
Ohio	0.56 to 0.70	0.93	0.91
Pennsylvania	0.45 to 0.53	0.76	0.90
Florida	0.37 to 0.48	0.63	0.82
Illinois	0.33 to 0.34	0.74	0.86
Texas	1.02 to 1.18	0.95	0.98
New York	1.02 to 1.38	0.99	0.99
California	0.47 to 0.65	1.01	0.98

Notes

[1]This paper works with the March 2005 vintage of state personal income.

[2]BEA does receive state-level average weekly hours and average hourly earnings data for manufacturing workers, which it used to produce a manufacturing earnings measures for its extrapolations over the sample period studied in this mimeo. For all other industries, employment data alone was used for the extrapolations.

[3]This removes from the weights the effect of aggregate wage and salary growth; if we did not do this more recent revisions in the sample may receive a substantially higher weight than older revisions.

[4]Another way to proceed would be to leave $\Delta\mathrm{WS}^p_{a,t}$ unaltered, but chose $\Delta\widehat{\mathrm{WS}}^l_{i-a,t}$ to minimize WMSTR and WMATR, or:

$$WMSTR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left((\Delta\mathrm{WS}^l_{a,t} - \Delta\mathrm{WS}^p_{a,t}) + \left(\Delta\mathrm{WS}^l_{i-a,t} - \Delta\widehat{\mathrm{WS}}^l_{i-a,t}\right)\right)^2,$$

and:

$$WMATR = \frac{1}{\sum_t \sum_j w_{j,t}} \sum_t \sum_i w_{i,t} \left| (\Delta\mathrm{WS}^l_{a,t} - \Delta\mathrm{WS}^p_{a,t}) + \left(\Delta\mathrm{WS}^l_{i-a,t} - \Delta\widehat{\mathrm{WS}}^l_{i-a,t}\right) \right|.$$

When minimizing squared deviations, the $\Delta\widehat{\mathrm{WS}}^l_{i-a,t}$ that minimize WMSIR are the same $\Delta\widehat{\mathrm{WS}}^l_{i-a,t}$ that minimize WMSTR, so the decision of whether or not to include the aggregate revisions is immaterial. To see this, note that:

$$\begin{aligned}
&\sum_i w_{i,t}\left((\Delta \mathrm{WS}^l_{a,t}-\Delta \mathrm{WS}^p_{a,t})+\left(\Delta \mathrm{WS}^l_{i-a,t}-\Delta \widehat{\mathrm{WS}^l_{i-a,t}}\right)\right)^2 \\
=\ &\sum_i w_{i,t}\begin{pmatrix} (\Delta \mathrm{WS}^l_{a,t}-\Delta \mathrm{WS}^p_{a,t})+\left(\Delta \mathrm{WS}^l_{i-a,t}-\Delta \widehat{\mathrm{WS}^l_{i-a,t}}\right)- \\ \sum_j w_{j,t}\left((\Delta \mathrm{WS}^l_{a,t}-\Delta \mathrm{WS}^p_{a,t})+\left(\Delta \mathrm{WS}^l_{j-a,t}-\Delta \widehat{\mathrm{WS}^l_{j-a,t}}\right)\right)\end{pmatrix}^2 \\
&+\left[\sum_j w_{j,t}\left((\Delta \mathrm{WS}^l_{a,t}-\Delta \mathrm{WS}^p_{a,t})+\left(\Delta \mathrm{WS}^l_{j-a,t}-\Delta \widehat{\mathrm{WS}^l_{j-a,t}}\right)\right)\right]^2 \\
\approx\ &\sum_i w_{i,t}\left(\Delta \mathrm{WS}^l_{i-a,t}-\Delta \widehat{\mathrm{WS}^l_{i-a,t}}\right)^2+\left[\Delta \mathrm{WS}^l_{a,t}-\Delta \mathrm{WS}^p_{a,t}\right]^2,
\end{aligned}$$

using $\sum_i w_{i,t}=1$ repeatedly, $\sum_i w_{i,t}\Delta \mathrm{WS}^l_{i-a,t}\approx 0$, which is very close to holding true in our data, and $\sum_i w_{i,t}\Delta\widehat{\mathrm{WS}^l_{i-a,t}}=0$, which we impose on our estimates. So for each period t, WMSTR equals WMSIR plus the aggregate revision, which is just a constant that will have no impact on the minimized choice of $\Delta\widehat{\mathrm{WS}^l_{i-a,t}}$. For absolute revisions, choice of WMATR versus WMAIR will have some impact on $\Delta\widehat{\mathrm{WS}^l_{i-a,t}}$, but given the result for squared revisions, there is no reason to believe this impact will be large; $\Delta\widehat{\mathrm{WS}^l_{i-a,t}}$ should be quite similar in either case.

[5]We also see that the variability of the second estimates are substantially larger than the variability of the latest ones, apparently revisions to seasonal factors after the second estimate dampen variation in the data considerably.

[6]In evaluating this assumption, it should be kept in mind that, after three years, the seasonal adjustment procedure is largely completed, and as discussed in the prior section, the source data in all vintages after the second remains the same, and is essentially a census of all wage and salary income.

[7]The corrections to the standard errors matter, as the uncorrected standard errors

were about 0.02.

[8]Specifically, I generated time series of the same length used in this paper, drawing values of x_t and u_t from a normal distribution (using Matlab 7.0), and computing $y_t = x_t\beta + u_t$, where $\beta = 0.6$. The distribution of x_t has variance $\sigma_x^2 = 0.5$, and I fix the variance of y_t at one by taking the distribution of u_t to have variance $\sigma_u^2 = 1 - \beta^2\sigma_x^2$; these variances approximately match up with the data on weighted summary statistics in table 1. I then repeat the rolling regression procedure used in this paper on the simulated data, comparing rolling regression results with those from extrapolation that assumes, incorrectly, that $\beta = 1$. I conducted 5000 of these simulations; MSIR from rolling regression was smaller than MSIR from extrapolation in 74% of these, and MAIR was smaller in 71%, similar percentages to the $\frac{37}{51} = 73\%$ and $\frac{39}{51} = 76\%$ observed in the data. Average $\frac{MSIR}{MSIR_c}$ and $\frac{MAIR}{MAIR_c}$ in the simulations were about 0.93 and 0.96, respectively, also similar to those found in table 2.

[9]In particular, we have:

$$
\begin{aligned}
\sum_i w_{i,t}\beta_{i,t}\Delta\mathrm{WS}^p_{i-a,t} &= \sum_i w_{i,t}\left(\sum_j w_{j,t}\beta_{j,t}\right)\Delta\mathrm{WS}^p_{i-a,t} \\
&\quad + \sum_i w_{i,t}\left(\beta_{i,t} - \sum_j w_{j,t}\beta_{j,t}\right)\Delta\mathrm{WS}^p_{i-a,t} \\
&= \overline{\beta_t}\sum_i w_{i,t}\Delta\mathrm{WS}^p_{i-a,t} + \sum_i w_{i,t}\left(\beta_{i,t} - \overline{\beta_t}\right)\Delta\mathrm{WS}^p_{i-a,t} \\
&= \sum_i w_{i,t}\left(\beta_{i,t} - \overline{\beta_t}\right)\Delta\mathrm{WS}^p_{i-a,t}
\end{aligned}
$$

with $\overline{\beta_t} = \sum_j w_{j,t}\beta_{j,t}$, so this sum will be large only if there is some systematic relation between the cross sectional variation in βs and cross sectional variation in growth rates; there is no reason to believe this is the case.

Figure 1: Betas by Year, Ordinary Least Squares and Least Absolute Deviations Estimates