Capacity Utilization As a Real-Time Predictor of Manufacturing Output

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The notion that aggregate output has both a permanent component and a transitory component is consistent with a wide range of business cycle theories. Insofar as the permanent component of output is observable in real time, the gap between current and permanent output will contain information useful in predicting future changes in output.

The empirical literature contains several efforts to predict output in this way. In a bivariate setting, Cochrane (1994) has shown that the permanent component of U.S. real gross domestic product (GDP) can be closely approximated by mean-adjusted real household consumption of nondurable goods and services and that the gap between current real output and mean-adjusted consumption has significant marginal explanatory power for future output growth. A procedure for approximating the permanent component of output using only current and lagged output observations is suggested by DeLong and Summers (1988, 459). In a limiting case, the DeLong and Summers formula reduces to using the historical maximum of output as a measure of permanent output. The implicit underlying assumption is that any decline in output is likely to be transitory. Beaudry and Koop (1993) report success including the difference between output and its historical maximum in forecasting equations for U.S. real GDP. Wynne and Balke (1992, 1993) use essentially the same approach to establish a tendency for deep recessions to be followed by strong recoveries.

In this article, I examine whether manufacturing capacity, as estimated by the Federal Reserve Board, is a useful measure of the permanent component of manufacturing output. Specifically, I consider whether manufacturing capacity utilization has marginal explanatory power for subsequent growth in manufacturing output. Except for a brief, illustrative aside, I use only real-time utilization data. The use of real-time data is critical. The Federal Reserve indices of capacity and utilization are subject to extensive revisions, which may extend back several years. Moreover, revision procedures are designed, quite consciously, to smooth capacity and to ensure that utilization is a stationary series. The effect is to incorporate information about future output in the revised capacity data. Real-time data, obviously, cannot incorporate information unavailable to analysts at the time.

The empirical results indicate that the Federal Reserve's initial capacity utilization releases do, indeed, contain useful information about future manufacturing output growth. Significant marginal explanatory power remains even after controlling for real-time estimates of lagged output growth, a measure of labor force utilization, and lagged changes in the Commerce Department's composite leading index. On the other hand, although the Federal Reserve's utilization measure appears to contain more useful information than does the Beaudry–Koop measure, the difference in information content is not statistically significant. These results hold regardless of whether one is trying to predict the Federal Reserve Board's initial estimate of output growth or a revised estimate. Using data available through the fourth quarter of 1995, the forecasting model developed in this article is predicting essentially no change in the level of manufacturing output during 1996.

The Federal Reserve indices of capacity and utilization[1]

For a given industry, the Federal Reserve Board obtains a series of reference end-of-year capacity estimates by dividing its output index for that industry by utilization rates taken from a biennial Census Bureau survey of manufacturing plants.[2] These reference estimates establish the long-term trend growth rate of the Board's published capacity index. Detrended year-to-year variations in the published capacity index for a given industry are determined by movements in the estimated capital stock for that industry or, less frequently, by movements in direct physical-unit capacity measures. Estimated capital stocks are calculated from Bureau of Economic Analysis surveys of capital spending plans using the perpetual inventory method. The capital stock estimates are subject to substantial revision every fifth year, when Census investment data become available. Capacity series are aggregated across industries, using the same value-added weights employed in the construction of the Board's aggregate output indices.

Monthly estimates of capacity are obtained by interpolating between end-of-year figures. It follows that within-year variation in capacity utilization largely reflects month-to-month movements in output (Shapiro 1989). Accordingly, this article uses only output, capacity, and utilization data reported for the fourth quarter of each year.

Although capacity and utilization data extend back to 1948, regular publication did not begin until 1968. [3] Hence, the analysis that follows is limited to a sample period that starts in 1968.

Predicting initial estimates of output growth

In this section, I look at whether the Federal Reserve's initial estimates of capacity utilization have real-time predictive power for its initial estimates of manufacturing output growth. To shed light on this question, I undertake a series of regressions of the form

$$(1) \qquad \Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 u_{t-1} + \alpha_3 z_{t-1},$$

over a sample period running from 1968 through 1994. Here, Δy_t denotes the change in the logarithm of manufacturing output from the fourth quarter of year $t - 1$ to the fourth quarter of year t, as published in the *Federal Reserve Bulletin* early in year $t + 1$, when data for the fourth quarter of year t first become available; Δy_{t-1} denotes the change in the logarithm of output from the fourth quarter of year $t - 2$ to the fourth quarter of year $t - 1$, as published early in year t; u_{t-1} denotes the logarithm of capacity utilization in the fourth quarter of year $t - 1$, as published early in year t; and z_{t-1} is any one of several lagged explanatory variables.[4] Lagged (real-time) capacity growth and additional lags of (real-time) output growth are not statistically significant when included on the right-hand-side of the estimated equation.

Column 1 of Table 1 presents results for the case in which $\alpha_3 \equiv 0$. The coefficient on the Federal Reserve's measure of capacity utilization is statistically significant at better than the 1-percent level. Its point estimate indicates that each 1-percent increase in utilization implies a nearly 57 basis-point decrease in output growth over the coming year.

In columns 2 and 3, z is the Beaudry–Koop measure of utilization that would have been observed in real time. That is, z_t is the real-time difference between the current log level of output and the logarithm of the historical maximum level of output. Introduced separately, as in column 2, the impact of the Beaudry–Koop measure on subsequent output growth is highly statistically significant. Each 1-percentage-point increase in output, relative to its historical maximum, is associated with a 1.1-percentage-point reduction in output growth over the coming year. In going from column 2 to column 3, the impact of the Beaudry–Koop measure drops sharply in magnitude and is no longer statistically significant. The Federal Reserve measure is also insignificant, but the magnitude of its coefficient is affected less and its t statistic is larger than that of the Beaudry–Koop measure. The adjusted R^2s and standard errors reported at the bottom of columns 1 and 2

Table 1
Predicting the Initial Estimate of Manufacturing Output Growth

Estimated equation: $\Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 u_{t-1} + \alpha_3 z_{t-1}$
Fourth-quarter data: 1967–94

	z						
	None	Beaudry–Koop		Avg. weekly hours		Leading index growth	
α_0	2.499***	–.0128	1.854	.397	1.975**	.0231***	1.650**
	(.771)	(.0161)	(1.432)	(.896)	(.875)	(.0082)	(.636)
α_1	.523**	.680**	.606**	.181	.428*	.046	.326*
	(.213)	(.262)	(.265)	(.256)	(.224)	(.148)	(.172)
α_2	–.568***	—	–.422	—	–.686***	—	–.373**
	(.177)		(.324)		(.200)		(.146)
α_3	—	–1.102***	–.365	–.0093	.0258	2.427***	2.012***
		(.381)	(.679)	(.0222)	(.0211)	(.518)	(.495)
Adj. R^2	.253	.207	.230	–.061	.268	.441	.546
SE	.0445	.0458	.0452	.0530	.0441	.0385	.0347
Q(6)	2.718	2.379	2.063	10.138	3.715	6.162	4.337

* Significant at the 10-percent level.
** Significant at the 5-percent level.
*** Significant at the 1-percent level.

confirm that the Federal Reserve utilization measure has greater marginal predictive power than does the Beaudry–Koop measure.

In columns 4 and 5, z is defined as average weekly hours of manufacturing production workers—a measure of labor force utilization.[5] The estimated coefficient of this variable is not statistically significant even in a regression with $\alpha_1 \equiv 0$. With α_1 unconstrained, the Federal Reserve capacity utilization measure is both statistically and economically significant, while the labor force utilization measure is not.

Finally, columns 6 and 7 report results for the case in which z_{t-1} is defined as the change in the logarithm of the Commerce Department's composite index of leading economic indicators, where this change is measured from September to December of year $t - 1$.[6] The change in the composite leading index (CLI) clearly has substantial marginal predictive power for future output growth.[7] However, including CLI growth in the forecasting equation does not eliminate the influence of capacity utilization as measured by the Federal Reserve Board.

Figure 1 shows fourth-quarter-over-fourth-quarter growth in manufacturing output, as initially reported by the Federal Reserve Board, along with predictions obtained from the forecasting equation of Table 1, column 7. With isolated exceptions, the forecasting equation appears to do a good job of capturing the qualitative pattern of output growth. Thus, in six of the seven years in which output was reported to have fallen, the model would have predicted either an output decline or zero growth (more precisely, growth of less than 0.5 percent). Only in 1981 would the model have stumbled badly, predicting 3.1 percent positive growth when output subsequently actually fell by 2.5 percent. Similarly, the model would have been qualitatively correct in nineteen of twenty years in which output was reported to have

Figure 1
Real-Time Growth in Manufacturing Output

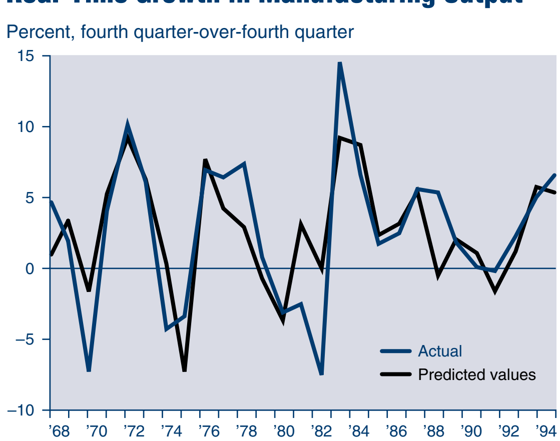


Table 2
Predicting the Final Estimate of Manufacturing Output Growth

Estimated equation: $\Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 u_{t-1} + \alpha_3 z_{t-1}$
Fourth-quarter data: 1967–94

	z						
	None	Beaudry–Koop		Avg. weekly hours		Leading index growth	
α_0	2.527***	–.0059	2.195	.533	2.082**	.0285***	1.650**
	(.757)	(.0161)	(1.413)	(.884)	(.866)	(.0079)	(.600)
α_1	.430*	.560**	.473*	.106	.349	–.052	.227
	(.209)	(.263)	(.261)	(.252)	(.222)	(.142)	(.163)
α_2	–.573***	—	–.498	—	–.673***	—	–.372**
	(.174)		(.320)		(.198)		(.138)
α_3	—	–1.056**	–.187	–.0125	.0219	2.490***	2.076***
		(.382)	(.670)	(.0220)	(.0209)	(.496)	(.467)
Adj. R^2	.255	.179	.225	–.068	.258	.472	.582
SE	.0437	.0459	.0446	.0524	.0436	.0368	.0328
Q(6)	1.157	5.963	5.038	11.839*	5.828	5.643	5.187

* Significant at the 10-percent level.
** Significant at the 5-percent level.
*** Significant at the 1-percent level.

increased. The glaring exception is 1988, when the model would have predicted a 0.5-percent output decline, and actual output growth was +5.4 percent.

Predicting final estimates of output growth

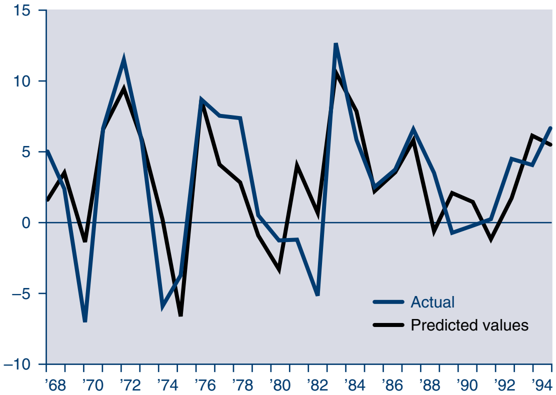
In Table 1, the dependent variable is manufacturing output growth as first reported by the Federal Reserve. Table 2 presents corresponding empirical results for the case in which the dependent variable is output growth as recorded in final revised data. Presumably, the final revised output data more accurately reflect actual economic developments. For most purposes, it is these data that are probably most relevant to policymakers.[8] On the right-hand side of the forecasting equation, I use exactly the same variables as before. In particular, on the right-hand side I continue to use only output and utilization data that would have been available to a forecaster in real time.

Both qualitatively and quantitatively, the results displayed in Table 2 are very similar to those reported in Table 1. The Federal Reserve's utilization series continues to have significant marginal predictive power in the presence of lagged output growth, in the presence of lagged labor force utilization, and in the presence of lagged growth in the Commerce Department's composite leading index. Neither lagged labor force utilization nor the Beaudry–Koop utilization measure has marginal predictive power in the presence of the Federal Reserve utilization index. While a head-to-head contest between the Federal Reserve and Beaudry–Koop utilization measures is inconclusive, results tend to favor the Federal Reserve measure. This tendency is even clearer in Table 2 than in Table 1.

Figure 2 is the revised-data counterpart of Figure 1. It shows how successfully one can predict final revised output growth using lagged CLI growth and initial estimates of lagged output

Figure 2
Revised Growth in Manufacturing Output

Percent, fourth quarter-over-fourth quarter



growth and capacity utilization. While the model's overall ability to predict final revised output growth—as measured by the model's adjusted R^2 or its standard error—is better than its ability to forecast the initial estimate of output growth, a comparison of Figures 1 and 2 suggests that the model does a somewhat poorer job of catching changes in the sign pattern of revised growth than it does catching the sign pattern of real-time output growth. Thus, in the revised data, eight years show declines in output. In only four of these eight years is growth predicted to be negative or zero (growth of less than 0.5 percent). In nineteen years, the final revised data show an expanding manufacturing sector. But in three of these nineteen years, the model predicts an output decline.

How important is it to use real-time data?

Analysts typically forecast in real time using equations estimated with revised data. There are two dangers associated with this practice. First, because revised right-hand-side data are used in estimation but not in forecasting, there is a danger that the in-sample predictive performance of the forecasting equation will significantly overstate the equation's actual performance in real time. Second, there is a danger that the actual forecasting performance of the equation will fall significantly short of the performance that would have been obtained had the equation been estimated correctly, using real-time data for the right-hand-side variables. This section argues that both of these dangers are serious when forecasting growth in manufacturing output using data on manufacturing capacity utilization.

Consider a regression of manufacturing output growth on lagged output growth, lagged capacity utilization, and the lagged change in the composite leading indicators, where all data are now revised:[9]

$$(2)\quad \underset{}{\Delta y_t} = \underset{(.665)}{1.985} + \underset{(.156)}{.249}\Delta y_{t-1} - \underset{(.152)}{.447}u_{t-1} + \underset{(.478)}{1.930}z_{t-1}.$$

$$\text{Adj. } R^2 = .598 \qquad \text{SE} = .0321$$

Coefficient estimates are broadly similar to those obtained when real-time data are used as right-hand-side variables. (Compare the estimates above with those reported in the last column of Table 1 and the last column of Table 2.) Here, however, substantially greater weight is placed on lagged utilization, and somewhat smaller weight is placed on the lagged change in the leading index. The coefficient of lagged output growth is smaller than that reported in Table 1 but greater than that reported in Table 2.

Are these differences in coefficient estimates of practical importance? Consider, first, an effort to forecast output growth as initially reported by the Federal Reserve. For this purpose, one would, ideally, substitute real-time data into the equation estimated in the last column of Table 1. Label the resultant forecasts "model 1." The more usual approach is to substitute real-time observations into the right-hand side of an equation like 2, above, which has been estimated using revised data. Call this approach "model 2." Not surprisingly, the standard error of model 2 forecasts is larger than the standard error of model 1 forecasts. For example, model 2's standard error is 0.0373 over the sample period, as compared with a standard error of 0.0347 for model 1. A formal encompassing test (see the box titled "Forecast Encompassing") indicates that this difference in forecast performance is statistically significant at the 10-percent level. In other words, the payoff to estimating the forecasting equation using real-time data is nontrivial.

Now consider an effort to forecast the Federal Reserve's final *revised* estimates of manufacturing output growth. In this case, there are a total of three modeling exercises to consider. First, a naive analyst might expect to be able to reproduce the performance of equation 2 itself. Call this purely hypothetical forecasting approach "model A." Second, the analyst could regress revised output growth on real-time observations of the right-hand-side variables, as in Table 2. Label the resultant forecasts "model B." More usually, the analyst would obtain forecasts by substituting real-time data into the right-hand side of equation 2. Call this approach "model C." Generally, one would expect model A to (appear to) outperform model B.[10] Invariably, the forecasts of model B will outperform those of model C. In the present instance, model A's standard error is 0.0321 (see equation 2, above), as compared with 0.0328 for model B (see Table 2, column 7) and 0.0339 for model C. Formal encompassing tests indicate that the difference in forecasting performance between model A and model C is statistically significant at the 10-percent level—meaning that the analyst who estimates the forecasting equation using revised data obtains a view of that equation's forecasting performance that is significantly too optimistic. However, neither the difference in performance between model A and model B nor the difference in performance between model B and model C is statistically significant.

Forecast Encompassing

The intuition underlying the Chong and Hendry (1986) forecast encompassing test is simple. Let Δy denote the variable being forecasted, and let Δy_1^f and Δy_2^f denote forecasts generated by two competing models. Consider the regression equation

$$\Delta y = \alpha \Delta y_1^f + (1 - \alpha)\Delta y_2^f + \epsilon,$$

where ϵ is a random-error term. If $\alpha \neq 0$, then Δy_1^f contains useful information for forecasting Δy that is not contained in Δy_2^f, and model 1 is said to "encompass" model 2. If $\alpha \neq 1$, then Δy_2^f contains useful information for forecasting Δy that is not contained in Δy_1^f, and model 2 encompasses model 1. If model 1 encompasses model 2, but model 2 fails to encompass model 1 (that is, if $\alpha = 1$), then model 1 is clearly superior for forecasting purposes. If model 1 is encompassed but is not encompassing (that is, if $\alpha = 0$), then it is model 2 that has clear superiority.

Two applications are considered in the main text. In the first application, Δy is defined as growth in manufacturing output as initially reported by the Federal Reserve. Model 1 is defined as the regression equation displayed in the last column of Table 1, which is estimated using real-time data. Model 2 is defined to be equation 2, estimated using revised data. For both models, real-time data are used on the right-hand side for forecasting purposes. The estimated value of α is 1.000, with standard error 0.496 and marginal significance level 0.054. It follows that model 1's performance is superior to that of model 2 at better than the 10-percent-significance level. That is, the forecasts generated by the equation estimated with real-time data are significantly superior to the forecasts generated by the equation estimated using revised data.

In the second application, Δy is defined as growth in manufacturing output as it appeared in August 1995, after numerous revisions. Three alternative forecasting models are considered. Model A is defined to be equation 2 under the unrealistic assumption that revised right-hand-side data are available for forecasting. Model B is the equation displayed in the last column of Table 2, estimated using real-time data and with real-time data substituted into the equation's right-hand side for forecasting purposes. Model C is equation 2 with real-time data substituted into the equation's right-hand side for forecasting purposes.

In a comparison of models A and C, the estimated value of α is 0.722, with standard error 0.380 and marginal significance level 0.068. It follows that model A's forecasting performance is superior to that of model C at better than the 10-percent-significance level. The proper interpretation of this result is that models estimated using revised data give a strongly misleading impression of how accurately one can forecast output growth. In a comparison of models B and C, the estimated value of α is 1.000, with standard error 0.725, and in a comparison of models A and B, the estimated value of α is 0.627, with standard error 0.490. In neither case does one model clearly dominate the other.

(For details, see the box titled "Forecast Encompassing.")

Thus, it would appear that in predicting growth in manufacturing output, there is a very real danger that forecasting equations estimated with revised utilization data will either (1) perform significantly worse than summary statistics from the regression would suggest or (2) perform significantly worse than would a forecasting equation estimated with real-time utilization data.

Forecasts for 1995 and 1996

The estimates reported in Tables 1 and 2 and the predictions displayed in Figures 1 and 2 extend only through 1994. How well did this simple forecasting model predict 1995 output growth? What is it predicting for 1996?

The answer to the first question is "very well, indeed." The initial Federal Reserve Board estimates of 1994 manufacturing output growth and 1994:4 manufacturing capacity utilization were 6.6 percent and 84.4 percent, respectively. CLI growth during the final three months of 1994, as reported early in March 1995, was 0.2 percent (not annualized). Combining these numbers with the coefficient estimates reported in Table 1, column 7, one obtains predicted output growth of 2.0 percent between the fourth quarter of 1994 and the fourth quarter of 1995—only 0.5 percentage point above the Federal Reserve Board's initial estimate of actual growth.

As of January 1996, the Federal Reserve Board estimated 1995 output growth and 1995:4 capacity utilization to be 1.5 percent and 82.0 percent, respectively. As of early March 1996, the CLI was reported to have fallen 0.4 percent in the final three months of 1995. According to the coefficient estimates recorded in Table 1, column 7, it follows that manufacturing output will likely expand by only 0.2 percentage points between the fourth quarter of 1995 and the fourth quarter of 1996—essentially no growth at all. Recall, however, that in 1974 a similar forecast was followed by a 4.3-percent output decline, while in 1988 a similar forecast was followed by a 5.4-percent output increase![11] More generally, the standard error associated with the output-growth forecasts of the model is large enough (roughly 3.5 percentage points) to cover a fairly wide range of outcomes.

Concluding remarks

This article tests whether the Federal Reserve Board's initial capacity utilization releases contain information useful in forecasting future growth in manufacturing output. Results suggest that initial utilization releases do indeed have significant predictive power for both initial and final estimates of output growth. Significant predictive power is evident even after controlling for the initial estimate of lagged output growth, lagged labor force utilization, and lagged growth in the Commerce Department's composite leading index. However, although the Federal Reserve's utilization measure appears to contain more useful information than does a utilization measure proposed by Beaudry and Koop, the difference in information content between the two measures is not statistically significant.

Together, the leading index, real-time lagged output growth, and real-time capacity utilization explain more than half the variation in the initial and final estimates of fourth quarter-over-fourth quarter manufacturing output growth. With a few important exceptions, the forecasting equations have also performed well in predicting the qualitative pattern of the initial output growth estimates. Data available early in the year suggest that the level of manufacturing output is likely to be essentially flat over 1996. However, the standard error attached to this forecast is such that one cannot rule out either a moderate expansion or a moderate contraction of manufacturing activity.

Notes

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1 The following discussion draws upon Raddock (1985, 1990).

2 The Census Bureau began its survey in 1974. Prior to then, the Federal Reserve Board relied on end-of-year utilization surveys conducted by McGraw-Hill/DRI and the Bureau of Economic Analysis. These surveys were discontinued in 1988 and 1983, respectively. The Board adjusts the level of the Census Bureau utilization rates to minimize any historical discontinuities between them and the McGraw-Hill/DRI rates.

3 Moreover, pre-1967 data are not fully consistent with data for subsequent years. In particular, both physical-unit capacity data and Bureau of Economic Analysis investment estimates receive substantially greater weight in the post-1966 calculations of capacity and utilization than in pre-1967 calculations (Shapiro 1989, 193–4; Raddock 1990).

4 Initial estimates of fourth-quarter manufacturing output and fourth-quarter capacity utilization are typically released in mid-January of the following year and appear in the March issue of the *Federal Reserve Bulletin.*

5 An alternative measure of labor force utilization—average weekly overtime hours in manufacturing—failed stationarity tests.

6 I use final revised leading index data in the regressions, rather than real-time data. Historically, the Commerce Department's leading index has been subject to two kinds of revisions. First, there are routine revisions to the CLI's component data series. Second, there are occasional changes in the structure of the CLI. Arguably, the first type of revision should not be a source of concern in the present context. The largest routine data revisions typically occur within the first few months following the CLI's initial release. In particular, the bulk of the routine revisions to fourth-quarter CLI growth are completed by the end of the first quarter of the following year. A two or three month delay in the availability of reliable CLI data might be significant if I were forecasting quarterly output growth, but here I am concerned only with output growth over four-quarter spans. As regards structural revisions, while the historical record of the CLI's current formulation may *over*state the CLI's future forecasting performance, the historical record of older formulations of the CLI would almost certainly *under*state the current CLI's future performance. I have chosen the alternative most likely to bias my results against finding a significant role for capacity utilization in the output forecasting equation.

7 Additional lagged changes in the composite leading index were not significant.

8 However, the Federal Reserve's initial published estimates of output growth may have an important influence on the investment and pricing decisions made by households and firms. Consequently, predicting the initial estimate of output growth is an exercise not without interest.

9 The data are for the fourth quarter of each year from 1968 through 1994, as published in August 1995.

10 That is, one would expect it to be easier to predict revised output growth using revised right-hand-side variables than using real-time right-hand-side variables.

11 Both of these estimates were later revised downward—to a 5.9-percent decline and a 3.5-percent increase, respectively.

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