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Why are initial estimates of productivity growth so unreliable?

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ABSTRACT

This paper argues that initial estimates of productivity growth will tend to be much less reliable than those of most other macroeconomic aggregates, such as output or employment growth. Two distinct factors complicate productivity measurement. (1) When production increases, factor inputs typically increase as well. Productivity growth is therefore typically less variable than output growth, meaning that measurement errors will tend to be *relatively* more important. (2) *Revisions* to published estimates of production and factor inputs tend to be less highly correlated than the published estimates themselves. This further increases the impact of data revisions on published productivity estimates.

To assess the extent of these problems in practice, we detail the importance of historical revisions to the most commonly-used measures of US aggregate productivity growth, expanding on previous empirical work by Aruoba (2008) and Anderson and Kliesen (2006). We find that such revisions have contributed substantially to policymakers' forecast errors for US productivity growth.

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Alan Greenspan on the measurement of US productivity growth

One would certainly assume that we would see this in the productivity data, but it is difficult to find it there. In my judgment there are several reasons, the most important of which is that the data are lousy.

Transcript: Meeting of the Federal Open Market Committee, December 19, 1995, p. 37.

The one thing we know about the official data on productivity is that they are wrong.

Transcript: Meeting of the Federal Open Market Committee, February 4–5, 1997, p. 101

The productivity numbers are very rough estimates because we are measuring a whole set of production outputs from one set of data and a whole set of labor inputs from a different set. That they come out even remotely measuring actual labor productivity is open to question....

Transcript: Meeting of the Federal Open Market Committee, March 25, 1998, p. 76

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1. Introduction

Productivity growth plays a key role in macroeconomics. Consumption and savings decisions at the core of macroeconomics depend on how perceived trends in productivity growth will affect future income streams. International differences in such trends in turn have profound influences on the balance of global saving and investment. Projected productivity growth is an important factor in forecasting long-run economic growth and therefore plays a central role in the management of public pension systems and government debt. It is an essential component in forecasting measures of economic slack and has therefore played a key role in the formulation of monetary policy.¹ The possibility of a persistent change in aggregate productivity growth casts a long shadow over many of the most important international and macroeconomic policy debates. For all these reasons, great effort is devoted to accurately measuring productivity and to the timely analysis of sources of productivity growth.

But when new productivity data are published and previously published figures are revised, conclusions about the size of productivity growth can change dramatically. For example, Fig. 1 shows the growth of labor productivity at four points in time (April 1974, April 1986, April 1992 and October 1996) and how these growth rates evolved over time as data were revised.² Over time, differences due to revisions become considerable, with measured productivity growth changing by a factor of two or more. As the figure makes clear, these variations are large relative to the apparent slowdown in productivity growth over time. Some of the largest changes to our estimates of the growth rate of productivity in April 1974 came more than 20 years later.

This paper investigates the statistical reliability of aggregate productivity estimates for the US. We try to explain why “recent” productivity growth estimates appear to be much less reliable than those of other series (particularly output and employment.) We argue that the importance and robust nature of revisions reflect a problem in the nature of productivity measurement. Productivity series are constructed as the residuals of cyclically-correlated measures of inputs and outputs. This causes measured productivity to be inherently less precise than either the input or output series from which it is derived.

While there is an extensive applied productivity literature, it is typically based on the most recent vintage and its emphasis is on understanding the sources of productivity growth rather than assessing the statistical reliability of productivity growth rate estimates. For example, Gordon (2000, 2010) and Jorgenson (2001) make no attempt to compare the magnitude of the effects that they find to their statistical reliability. Jin and Jorgenson (2010), who propose and apply a latent variable approach, make no mention of the precision or statistical significance of their results. As a rule their analyses effectively ignore the possibility of future data revision. The same critique applies to macroeconomic modeling exercises, such as the influential work of Smets and Wouters (2007), who ignore data revision in the estimation/calibration of their model. The studies of Field (2010) on the

¹ For example, Anderson and Kliesen (2010) argue that “The increasingly rapid productivity growth that began in the 1990s was the defining economic event of the decade and a major topic of debate among Federal Reserve policymakers.” As they document in Anderson and Kliesen (2010, 2012) debates within the FOMC centered on the fact that initial estimates of aggregate productivity growth during this period were quite low and were revised upwards only many years later.

² Labor productivity growth is here measured by the change over 20 quarters in the natural logarithm of output per hour in the private business sector.

procyclicality of multi-factor productivity (MFP) in the United States over the period 1890–2004, and of Galí and van Rens (2014) on the vanishing procyclicality of postwar US labor productivity also ignore data revision and differences in the reliability of the series that they compare.

Most of the existing literature on data revision in productivity growth has examined the closely related question of estimating and testing time-varying trend productivity growth. See e.g. Edge et al. (2007), Kahn and Rich (2007), Benati (2007) and van Norden (2005, 2011). However, there has been surprisingly little formal study of the systematic impact of data revision on the reliability of productivity growth statistics. For example, analysts studying recent productivity data would be interested to know (i) how large revisions to the latest figures may be, (ii) the expected size of any revisions, (iii) how the size of the expected revisions decreases over time, and (iv) how much time should pass before figures can be considered “reliable.”³ Aruoba (2008) analyses output per hour in the manufacturing sector and reports that revisions to annual growth rates had a standard deviation of 1.3%. He also finds that those revisions fit neither the “news” nor the “noise” models of measurement error.⁴ Anderson and Kliesen (2006) find mean absolute revisions in annual productivity growth in the range of 1–2%, and that measures covering more of the economy have smaller revisions. They also find that most of the revisions in output per hour worked comes from revisions to output rather than revisions to hours worked.

In line with the applied productivity literature we characterize the size and behavior of annual data revisions. We also consider the characteristics of revisions in long-run productivity growth to stress the link to the literature on estimating and testing time-varying trend productivity growth. We document the contribution of revisions in both annual and long-run productivity growth to overall uncertainty in productivity forecasts. We find that data revisions are economically important, with an 80% confidence interval for annual growth rates ranging from 2% to 6% wide and noise/signal ratios typically in the range of 0.5–1.0. There is no particular tendency for revisions to become less important as we restrict our attention to parts of the economy where productivity is easier to measure, such as manufacturing, or as we vary our definition from output-per-employee to output-per-hour to multi-factor productivity. Substantial revisions often occur years after the initial data release, which contributes significantly to the overall uncertainty policymakers face. Comparable results are found for revisions in long-run productivity growth. Results from Federal Reserve staff economic projections show that these revisions also add considerable uncertainty to short-term economic forecasts.

Our work is related to two other lines of research on policy formulation and measurement problems. One series of papers (summarized by Croushore (2011)) has examined the impact of macroeconomic data revision on macroeconomic policy. With only two exceptions (mentioned above) however, such work has both neglected productivity data and been limited to quarterly or annual growth rates. In a series of papers, Orphanides has examined the impact of output gap mismeasurement on historical interpretations of US monetary policy and how measurement uncertainty alters the trade-offs facing policymakers.⁵ The literature which followed has examined the degree of uncertainty related to various measures of the business cycle and its implications for policy formulation and modeling. Our findings on productivity revisions underscore the resulting need for macroeconomic models and policies which incorporate measurement uncertainty.

The remainder of the paper is structured as follows. Section 2 uses simple variance decompositions to show the relationship between the reliability of initial productivity estimates and that of the underlying measurements of inputs and outputs. It shows that positively correlated movements in input and output measures will exacerbate measurement errors in the derived estimates of productivity. This means that productivity may be much less precisely estimated than either the input or the output data upon which it depends. Section 3 discusses the characteristics of historical data revisions of different US productivity measures and considers whether initial estimates of productivity growth seem to be significantly biased as well as other revision characteristics. Section 4 describes the Greenbook forecast data and discusses the implications of data revision for Greenbook projections. Section 5 concludes.

2. On the reliability of productivity growth estimates

To better understand the reliability of productivity growth estimates and the scope for their improvement, we trace the sources of their revisions. Productivity growth can be decomposed in several ways. Corrado and Slifman (1999), for example, decompose aggregate productivity growth by sector. Here we decompose the noise/signal ratios of productivity measures to understand their relationship to the reliability of the underlying series used to calculate productivity.

We begin by defining the noise to signal ratio

$$N/S \equiv \frac{\sqrt{(T^{-1} \cdot \sum_t r_t^2)}}{\hat{\sigma}}, \quad (1)$$

where r_t is the revision in the published estimate for any series for period t and $\hat{\sigma}$ is the standard deviation of the current vintage of the published series. Note that the numerator is generally greater than the standard deviation of revisions because the former

³ This situation contrasts with the analysis of potential output, for example, where research has emphasized the degree to which estimated deviations of actual output from potential are revised *ex post*. As a result, some central banks now communicate such estimates in the form of “fan charts” or confidence intervals to emphasize their uncertainty.

⁴ “Noise” implies that measurement errors are uncorrelated with the unobserved “true” value; “news” implies that measurement errors are uncorrelated with available information. We discuss both in more detail below.

⁵ For example, see Orphanides (2001).

Table 1
Decomposing noise/signal ratios: annual labor productivity growth.

Output/employment	
(A) $\frac{\sum_t (R_t^Y)^2}{\sum_t (Y_t - \bar{Y})^2}$	0.19
(B) $\frac{\sum_t (Y_t - \bar{Y})^2}{\sum_t (Z_t - \bar{Z})^2}$	3.40
(C) $\frac{\sum_t (R_t^L)^2}{\sum_t (L_t - \bar{L})^2}$	0.09
(D) $\frac{\sum_t (L_t - \bar{L})^2}{\sum_t (Z_t - \bar{Z})^2}$	1.68
(E) $-2 \cdot \frac{\sum_t R_t^Y \cdot R_t^L}{\sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L})}$	0.07
(F) $\frac{\sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L})}{\sum_t (Z_t - \bar{Z})^2}$	2.04
(A) · (B) + (C) · (D) + (E) · (F)	0.94

will include any non-zero mean in the revisions. Revisions are defined as

$$r_t^{\tau_1, \tau_2} \equiv x_t^{\tau_2} - x_t^{\tau_1},$$

where t indicates the time period for which x is estimated and τ_1 and τ_2 indicate the periods at which the estimates were published.

Defining $\phi \equiv N/S$ and R_t^Z as the revision in variable Z at time t , we have

$$\phi^2 \equiv \sum_t (R_t^Z)^2 / \sum_t (Z_t - \bar{Z})^2,$$

where $\bar{Z} \equiv E(Z)$. Now suppose $Z_t \equiv Y_t - L_t$. Then we have

$$\begin{aligned} \phi^2 &= \frac{\sum_t (R_t^Y - R_t^L)^2}{\sum_t (Z_t - \bar{Z})^2} = \frac{\sum_t ((R_t^Y)^2 + (R_t^L)^2 - 2 \cdot R_t^Y \cdot R_t^L)}{\sum_t (Z_t - \bar{Z})^2} = \frac{\sum_t (R_t^Y)^2}{\sum_t (Z_t - \bar{Z})^2} + \frac{\sum_t (R_t^L)^2}{\sum_t (Z_t - \bar{Z})^2} - 2 \frac{\sum_t R_t^Y R_t^L}{\sum_t (Z_t - \bar{Z})^2} \\ &= \frac{\sum_t (R_t^Y)^2}{\sum_t (Y_t - \bar{Y})^2} \cdot \frac{\sum_t (Y_t - \bar{Y})^2}{\sum_t (Z_t - \bar{Z})^2} + \frac{\sum_t (R_t^L)^2}{\sum_t (L_t - \bar{L})^2} \cdot \frac{\sum_t (L_t - \bar{L})^2}{\sum_t (Z_t - \bar{Z})^2} - 2 \cdot \frac{\sum_t R_t^Y \cdot R_t^L}{\sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L})} \cdot \frac{\sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L})}{\sum_t (Z_t - \bar{Z})^2} \end{aligned}$$

This last equation relates ϕ^2 , the squared noise–signal ratio for Z , to the (squared) noise–signal ratio for its components Y and L , as well as a covariance term in their revisions. When revisions to Y and L both have mean zero and are uncorrelated (so that $\sum_t R_t^Y \cdot R_t^L = 0$), then ϕ^2 is the just weighted average of the squared noise–signal ratios of the two components, where the weights are the ratios of their variances to that of Z . In the general case, we have an additional term that depends on both the relative importance of the covariance of Y and L to the overall variance of Z , and the cross-moment of their revisions ($\sum_t R_t^Y \cdot R_t^L$).

Table 1 shows the noise/signal decomposition for annual labor productivity growth in the US. The first point to note is that while ϕ^2 for labor productivity (Z) is close to one, for output growth Y and for employment growth L its values are less than 20% and the cross-moment of their revisions is smaller still. The reason that revisions in labor productivity growth are relatively much more important than those in either Y or L is simply that productivity growth is much less variable than either of its components. The results in the table also imply that revisions in output growth are the dominant contributor to revisions in labor productivity; in the absence of revisions to employment growth ($R_t^L = 0$), ϕ^2 for labor productivity would be equal to $0.19 \cdot 3.40 = 0.65$.

Another way to understand these results is to use a slightly different decomposition. Defining $\sigma_x^2 \equiv T^{-1} \cdot \sum_t (x_t - \bar{x})^2$ and $s_x^2 \equiv T^{-1} \cdot \sum_t (R_t^x)^2$, the definition of Z_t then gives us

$$\begin{aligned} \sigma_Z^2 &= \sigma_Y^2 + \sigma_L^2 - 2 \cdot T^{-1} \cdot \sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L}) \\ s_Z^2 &= s_Y^2 + s_L^2 - 2 \cdot T^{-1} \cdot \sum_t R_t^Y \cdot R_t^L \\ \therefore \phi_Z^2 &= \frac{s_Y^2 + s_L^2 - 2 \cdot T^{-1} \cdot \sum_t R_t^Y \cdot R_t^L}{\sigma_Y^2 + \sigma_L^2 - 2 \cdot T^{-1} \cdot \sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L})}. \end{aligned}$$

Using

$$\begin{aligned} \rho_{YL} &\equiv (T \cdot \sigma_Y \cdot \sigma_L)^{-1} \cdot \sum_t (Y_t - \bar{Y}) \cdot (L_t - \bar{L}) \quad \text{and} \\ \gamma_{YL} &\equiv (T \cdot s_Y \cdot s_L)^{-1} \cdot \sum_t R_t^Y \cdot R_t^L, \end{aligned}$$

we can rewrite this in the form

$$\phi_Z^2 = \frac{s_Y^2 + s_L^2 - 2 \cdot s_Y \cdot s_L \cdot \gamma_{YL}}{\sigma_Y^2 + \sigma_L^2 - 2 \cdot \sigma_Y \cdot \sigma_L \cdot \rho_{YL}}.$$

From this last expression, we can see that

- $d\phi^2/d\gamma < 0$, because revisions tend to cancel out.
- $d\phi^2/d\rho > 0$, because there is less variability in the signal.

In [Table 1](#) we show that labor productivity has a higher noise–signal ratio than either output or employment. We interpret this as evidence that correlations in output and employment (ρ) are more important than the comovements in their revisions (γ). This is not surprising, given that employment data are an important input into preliminary estimates of output. As other data become available over time, differences between output and employment movements can be better discerned, which in turn is reflected in important revisions to implied labor productivity.

It is also straightforward to generalize the decomposition to the case where Z is a linear combination of more than two variables; we provide a derivation in the [Appendix](#). Moving from labor productivity to Multi-Factor Productivity (MFP) adds another possible source of revision: the capital stock. Capital stock estimates are heavily dependent on estimates of real investment, which themselves are among the most heavily revised portions of the national accounts. There appears to be a consensus that capital stock estimates are the most imprecise component of MFP estimates, but we are unaware of any systematic evidence on the size of their revisions. If MFP growth estimates are to be more reliable than labor productivity growth estimates, it must be the case that the uncertainty inherent in capital stock estimates serves to reduce the overall estimation error in the other two components. Below, we also compare the reliability of MFP growth estimates to those of labor productivity.

The above decompositions clearly explain why productivity growth estimates appear to be much less reliable than either the input or output series upon which they are based. This does not reflect any particular failing on behalf of government statistical agencies. The same type of problem arises for other economic series which are constructed as the residuals of two correlated series, such as Savings (Income – Consumption) or the Balance of Trade (Exports – Imports). This also implies that improvements in the precision in initial productivity estimates would seem to require much larger improvements in the underlying input and output measures from which they are derived. Given past efforts aimed at improving productivity measurement (and current fiscal priorities in the US and many other economies), further improvement is likely to be difficult.

3. Measures of productivity growth

No single measure of productivity is best for all purposes and care needs to be taken in matching the appropriate productivity measure to the problem at hand. Aggregate labor productivity, rather than aggregate or sectoral total factor productivity, is the relevant concept for many of the problems we mentioned at the outset. For consumption/savings decisions, individuals are concerned about the productivity of their labor, whether this is due to variations in total factor productivity or capital deepening. The same argument applies to studies of pension system solvency and, to some extent, to the management of public debt.⁶

[Table 2](#) lists the details of our US productivity measures, including data source, span of time series available and the range of vintages studied. Our five measures include one measure of multifactor productivity (MFP) and four measures of labor productivity. MFP is also the only annual series; all the rest are quarterly. Two series cover only the manufacturing sector, while the remainder are broad measures covering most or all of the economy. The output per hour measures capture data revisions from 1968 onward, while the manufacturing measures capture revisions only from the mid 1990s onward. Note that, as of October 2010 the most recent observation for multifactor productivity is the 2007 figure, which makes this measure less suited for practical policy analysis and forecasting.

[Figs. 2](#) and [3](#) show first releases and total revisions for our five productivity measures using both annual growth rates and 5-year growth rates. The similarity between output per hour of the private business sector and the non-farm business sector, the middle panel of both figures, reflects the similarity in their coverage.

Some have argued that many data revisions do not reflect uncertainty or measurement errors, but simply definitional changes (e.g., due to a change in base-year weights) in what is being measured. However, this argument confuses the operational definition that a statistical agency chooses for an official statistic (which varies as the agency's methodology changes) with the underlying economic concept that it attempts to estimate. For example, the economic concept of output that [Woodford \(2003\)](#) uses is not notably different from that used by [Sargent \(1979\)](#), although the narrow definition of the statistics used to estimate it underwent major changes in that time (e.g., from GNP to GDP and fixed weights to chain-weighting, to name but two). By including revisions due to changes in such operational definitions, we capture uncertainty about the best way to estimate an economic concept. While recent decades have seen much effort devoted to the improvement of official US aggregate productivity measures, many approximations and *ad hoc* assumptions continue to be used in the production of official statistics. ([Syverson \(2011, Section 2.2\)](#) provides a compact overview.) There is no reason to believe that methodological change will cease.

⁶ Consider the simple case of a government that can tax labor or capital. In an open economy, the ability to tax capital may be highly constrained by its high degree of international mobility, forcing governments to rely at the margin on labor taxes to manage their debts. The growth rate of the tax base will then be a function of labor productivity rather than total factor productivity.

Fig. 2. First releases (solid blue line) and total revisions (thick solid red line) in annual US productivity growth. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. First releases (solid blue line) and total revisions (thick solid red line) in 5-year US productivity growth. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Measures of US productivity growth: data.

Measure	Sector	Source	First/last period	First/last vintage
GDP per employee	All	PHIL FRB (GDP) ALFRED (empl.)	1980Q1–2009Q2	1991Q4–2009Q3
Output per hour	Business	ALFRED	1947Q1–2010Q2	1968M5–2010M9
Output per hour	Non-farm business	ALFRED	1947Q1–2010Q2	1968M5–2010M9
Output per hour	Manufacturing	ALFRED	1949Q1–2010Q2	1997M3–2010M9
Multifactor productivity	Manufacturing	ALFRED	1949–2007	1996M1–2010M2

Sources: PHIL FRB refers to the Philadelphia Federal Reserve Bank's Real-Time Data Set for Macroeconomists; ALFRED refers to the Federal Reserve Bank of St. Louis ALFRED data base.

3.1. Descriptive statistics

Data revisions may be conveniently classed into three types:

1. initial revisions in the first few vintages,
2. seasonal revisions due to updated seasonal factors and the confrontation of quarterly with annual information, and
3. historical or comprehensive revisions, related to changes in statistical methodology, etc.

Initial and seasonal revisions are regular and recurring, i.e., can in principle be modeled and forecast. Historical revisions are much more difficult to handle. Redefinitions like changes of base years do not cause many difficulties; however, methodological changes are much more difficult to handle. The distinction of revisions into these types requires careful handling of the real-time data and in many cases direct access to the officials of the statistical agency. We do not attempt to distinguish these different sources of revisions and instead simply examine how revisions change over time.

Tables 3 and 4 show descriptive statistics for cumulative productivity growth rates over 4 and 20 quarters, respectively, for different revision periods. In addition to showing the mean growth rate based on the current data vintage (CV) as listed in Table 2, the tables show the mean revision, the standard deviation of revisions, their extreme values, the 80% confidence interval, i.e., the revision's 10th and the 90th percentile, and their noise to signal ratio (N/S). The panels in each table correspond to different measures of productivity. The first line in each panel analyses total revisions ($\{r_t^{t+1,T}\}$ for $t = 1, \dots, T - 1$). The subsequent lines provide additional detail on the behavior of revisions over time, analyzing the revisions that occur in the first year after the initial release ($\{r_t^{t+1,t+5}\}$), one to five years after the initial release ($\{r_t^{t+5,t+21}\}$), more than one year after the initial release ($\{r_t^{t+5,T}\}$), and more than five years after the initial release ($\{r_t^{t+21,T}\}$).

Looking first at Table 3, we observe that mean revisions in all measures are always much less than 1% per year and often close to 0.1%. Revisions, however, have a wide range, with minimum and maximum revisions usually lying in the range of -3.0% to 4.0% , and 80% confidence intervals rise from just under 2% for GDP per employee to roughly 3% for broad measures of output per hour and over 5% for output per hour in manufacturing. These ranges are potentially large when compared to movements in annual productivity growth; the revisions also give noise to signal (N/S) ratios between 0.7 and 1.1. While revisions made in the first year following the initial release are not particularly small for any of the five series, in most cases they contribute relatively less of the overall uncertainty than revisions that come later.

One might hope that revisions might be relatively less important if we looked at productivity growth over a longer period. Table 4 provides results comparable to those just discussed for growth in productivity measured over five years (20 quarters) rather than one. Although results for individual series vary, overall we have similar results. While mean revisions are comparatively small, their variability (measured by their standard deviation, or 80% confidence interval, or range, or N/S) is not. Again, important revisions continue to arrive long after the initial data release.

3.2. News, noise and bias

The nature of data revisions has been much debated.⁷ Two polar views exist:

(i) Data revisions contain “news”: data are optimal forecasts, so revisions are orthogonal to earlier releases and therefore are not forecastable, so that

$$y_t^{CV} = y_t^{t+1} + v_t^{t+1}, \quad \text{cov}(y_t^{t+1}, v_t^{t+1}) = 0, \quad (2)$$

where y_t^{CV} is the current vintage estimate of y at time t , and y_t^{t+1} is the first release of y at time t (assuming a one-period publication lag).

(ii) Data revisions reduce “noise”: data are measured with error, so revisions are orthogonal to final data, which allows revisions to be forecastable. This implies

$$y_t^{t+1} = y_t^{CV} + \epsilon_t^{t+1}, \quad \text{cov}(y_t^{CV}, \epsilon_t^{t+1}) = 0. \quad (3)$$

⁷ The debate was initiated by Mankiw et al. (1984) and Mankiw and Shapiro (1986). Recent contributions included Faust et al. (2005), Swanson and van Dijk (2006) and Aruoba (2008). Jacobs and van Norden (2011) provide a brief survey.

Table 3

Measures of annual US productivity growth: descriptive statistics.

	CV	Revisions					N/S
	Mean	Mean	St. dev.	Min	Max	80%-interval	ratio
<i>Labor productivity: output/employment</i>							
Total revisions	0.017	0.000	0.009	−0.024	0.016	−0.009; 0.010	0.95
1st yr revisions	0.017	−0.001	0.005	−0.015	0.009	−0.008; 0.005	0.52
1st to 5th yr revisions	0.017	−0.001	0.008	−0.023	0.012	−0.010; 0.007	0.87
> 1st yr revisions	0.017	0.000	0.007	−0.022	0.014	−0.009; 0.010	0.79
> 5th yr revisions	0.017	0.002	0.003	−0.002	0.009	−0.001; 0.007	0.41
<i>Business sector: output per hour of all persons</i>							
Total revisions	0.021	0.002	0.013	−0.034	0.043	−0.012; 0.017	0.76
1st yr revisions	0.021	0.000	0.008	−0.026	0.031	−0.010; 0.007	0.46
1st to 5th yr revisions	0.021	−0.001	0.008	−0.022	0.022	−0.010; 0.010	0.51
> 1st yr revisions	0.021	0.002	0.011	−0.019	0.034	−0.010; 0.015	0.64
> 5th yr revisions	0.021	0.004	0.008	−0.018	0.030	−0.005; 0.013	0.53
<i>Nonfarm business sector: output per hour of all persons</i>							
Total revisions	0.020	0.002	0.012	−0.031	0.034	−0.012; 0.018	0.71
1st yr revisions	0.020	0.000	0.007	−0.026	0.026	−0.010; 0.007	0.43
1st to 5th yr revisions	0.020	−0.002	0.009	−0.022	0.021	−0.013; 0.011	0.51
> 1st yr revisions	0.020	0.002	0.011	−0.021	0.031	−0.012; 0.015	0.63
> 5th yr revisions	0.020	0.005	0.008	−0.018	0.030	−0.005; 0.014	0.53
<i>Manufacturing sector: output per hour of all persons</i>							
Total revisions	0.037	−0.003	0.020	−0.039	0.041	−0.036; 0.021	0.78
1st yr revisions	0.037	0.002	0.009	−0.023	0.023	−0.008; 0.013	0.34
1st to 5th yr revisions	0.037	−0.005	0.017	−0.036	0.019	−0.030; 0.016	0.66
> 1st yr revisions	0.037	−0.006	0.017	−0.037	0.018	−0.030; 0.017	0.70
> 5th yr revisions	0.037	0.002	0.007	−0.012	0.020	−0.005; 0.012	0.27
<i>Manufacturing – multifactor productivity</i>							
Total revisions	0.021	−0.002	0.017	−0.034	0.036	−0.027; 0.016	1.07
1st yr revisions	0.021	0.001	0.017	−0.030	0.047	−0.022; 0.014	1.07
1st to 5th yr revisions	0.021	−0.004	0.010	−0.019	0.017		0.66
> 1st yr revisions	0.021	−0.004	0.011	−0.021	0.016	−0.020; 0.013	0.75
> 5th yr revisions	0.021	−0.001	0.011	−0.020	0.022		0.66

Notes: CV stands for current vintage. The 80% interval gives the values for the 10th and the 90th percentiles. The N/Sratio is the noise to signal ratio as defined in Eq. (1).

We can test the above hypothesis with Mincer and Zarnowitz (1969) regression of the form

$$y_t^{CV} - y_t^{t+1} = \alpha_1 + \beta_1 y_t^{CV} + \varepsilon_t^{t+1}. \quad (4)$$

The null hypothesis that measurement errors are independent of true values ($\alpha_1 = 0$, $\beta_1 = 0$) may be tested with a Wald test; since the errors may suffer from heteroskedasticity and autocorrelation, robust standard errors are typically used.

The analogous test of the “news” model regresses the measurement error (e.g. $y_t^{CV} - y_t^{t+1}$) on a constant and the first release

$$y_t^{CV} - y_t^{t+1} = \alpha_2 + \beta_2 y_t^{t+1} + v_t^{t+1}. \quad (5)$$

The similar null hypothesis ($\alpha_2 = 0$, $\beta_2 = 0$) now tests whether data revisions are predictable. The two null hypotheses are mutually exclusive but they are not collectively exhaustive, i.e. we may be able to reject both hypotheses, particularly when the constant in both test equations differs from zero (see Aruoba, 2008, Appendix A.2).

Tables 5 and 6 list the estimation outcomes for Eqs. (4) and (5) for annual productivity growth and long-run (5-year) productivity growth. Testing annual productivity growth, we reject the null hypothesis that revisions are “news” at the 5% significance level for our three economy-wide measures of productivity, but not for our two measures of manufacturing. We reject the null hypothesis that revisions eliminate “noise” in all cases except that of MFP in manufacturing. When we test five-year productivity growth rates, we reject the “noise” model in every case and the “news” model in three of our five cases.

In addition, test outcomes for bias are included in the tables. We report the estimate of the constant in a regression of the total revision on a constant with Newey–West HAC standard outcomes. Total revisions in annual productivity growth are not significantly biased for any US productivity measure except GDP per employee. In contrast, using 20Q growth rate revisions we find significant bias in revisions for all productivity measures except for GDP per employee and for output per hour in the manufacturing sector.

4. Greenbook projections

In this section we compare the size of data revisions to the size of productivity growth rate forecast errors to examine the relative importance of data revisions from a policy perspective. The forecasts that we analyse here are those prepared by the staff of the US Federal Reserve Board for each meeting of the Federal Open Market Committee (FOMC) as part of their regular

Table 4

Measures of long-run (5 year) US productivity growth: descriptive statistics.

	CV	Revisions					N/S
	Mean	Mean	St. dev.	Min	Max	80%-interval	ratio
<i>Labor productivity: output/employment</i>							
Total revisions	0.085	0.009	0.018	−0.020	0.041	−0.012; 0.035	1.02
1st yr revisions	0.085	−0.002	0.011	−0.028	0.023	−0.017; 0.014	0.57
1st to 5th yr revisions	0.085	0.004	0.014	−0.020	0.029	−0.015; 0.026	0.74
> 1st yr revisions	0.085	0.012	0.013	−0.014	0.039	−0.004; 0.032	0.90
> 5th yr revisions	0.085	0.012	0.009	−0.003	0.032	0.002; 0.027	0.76
<i>Business sector: output per hour of all persons</i>							
Total revisions	0.101	0.014	0.020	−0.045	0.076	−0.010; 0.038	0.69
1st yr revisions	0.101	−0.001	0.012	−0.054	0.027	−0.014; 0.012	0.32
1st to 5th yr revisions	0.101	−0.002	0.016	−0.040	0.042	−0.023; 0.022	0.45
> 1st yr revisions	0.101	0.016	0.018	−0.016	0.075	−0.006; 0.040	0.66
> 5th yr revisions	0.101	0.021	0.016	−0.022	0.066	−0.002; 0.040	0.73
<i>Nonfarm business sector: output per hour of all persons</i>							
Total revisions	0.098	0.014	0.020	−0.039	0.075	−0.010; 0.039	0.68
1st yr revisions	0.098	−0.001	0.012	−0.051	0.028	−0.014; 0.013	0.32
1st to 5th yr revisions	0.098	−0.003	0.017	−0.042	0.040	−0.023; 0.023	0.47
> 1st yr revisions	0.098	0.016	0.018	−0.016	0.075	−0.006; 0.041	0.66
> 5th yr revisions	0.098	0.022	0.017	−0.021	0.068	−0.002; 0.042	0.75
<i>Manufacturing sector: output per hour of all persons</i>							
Total revisions	0.190	−0.006	0.027	−0.053	0.052	−0.034; 0.031	0.59
1st yr revisions	0.190	−0.002	0.020	−0.039	0.047	−0.032; 0.020	0.43
1st to 5th yr revisions	0.190	−0.016	0.024	−0.048	0.031	−0.046; 0.016	0.62
> 1st yr revisions	0.190	−0.004	0.020	−0.040	0.030	−0.034; 0.025	0.43
> 5th yr revisions	0.190	0.017	0.017	−0.003	0.044	−0.001; 0.039	0.52
<i>Manufacturing – multifactor productivity</i>							
Total revisions	0.083	−0.013	0.020	−0.052	0.022	−0.048; 0.009	0.74
1st yr revisions	0.083	−0.002	0.017	−0.042	0.034	−0.030; 0.014	0.52
1st to 5th yr revisions	0.083	−0.014	0.014	−0.037	0.004		0.63
> 1st yr revisions	0.083	−0.012	0.016	−0.046	0.008	−0.042; 0.004	0.62
> 5th yr revisions	0.083	−0.003	0.013	−0.030	0.013		0.40

Notes: CV stands for current vintage. The 80% interval gives the values for the 10th and the 90th percentiles. The N/S ratio is the noise to signal ratio as defined in Eq. (1).

Table 5

News/noise/bias test outcomes: total revisions in annual productivity growth.

Measure	News			Noise			Bias
	α_2	β_2	$\alpha_2 = 0, \beta_2 = 0$	α_1	β_1	$\alpha_1 = 0, \beta_1 = 0$	
GDP/EMP	−0.0004 (0.0026)	−0.2152 (0.1537)	[0.0186]	−0.0089 (0.0019)	0.2608 (0.1315)	[0.0000]	−0.0048 (0.0017)
OPH: Bus.	−0.0076 (0.0021)	0.3043 (0.0646)	[0.0000]	0.0031 (0.0025)	−0.2413 (0.0809)	[0.0038]	−0.0019 (0.0017)
OPH: NFB	−0.0065 (0.0019)	0.2724 (0.0612)	[0.0001]	0.0023 (0.0023)	−0.1994 (0.0740)	[0.0117]	−0.0017 (0.0015)
OPH: MFG	−0.0044 (0.0071)	0.1919 (0.1512)	[0.3769]	0.0205 (0.0075)	−0.4690 (0.1532)	[0.0134]	0.0033 (0.0045)
MFP: MFG	−0.0115 (0.0075)	0.5831 (0.2958)	[0.1323]	0.0120 (0.0069)	−0.4728 (0.2591)	[0.2208]	0.0020 (0.0034)

Notes: OPH stands for output per hour, Bus. for the Business sector, NFB for non-farm business sector, MFG manufacturing, and MFP is multifactor productivity. Newey–West HAC standard errors between brackets; p -Values of Wald (F) tests between square brackets.

Greenbook projections.⁸ Their forecasts for growth in Output per Hour in the Non-Farm Business sector (OPH-NFB) are available from the Federal Reserve Bank of St. Louis' ALFRED database.

These forecasts for quarterly growth at annual rates from 0 to 10 quarters ahead represent projections prepared for FOMC meetings from 11 January 1978 to 8 December 2004, for a total of 224 meetings.⁹ The projection horizon varies over time and generally tends to increase, with the result that a full 224 forecasts are available at horizons from 0 to 4 quarters,

⁸ Descriptions of *Current Economic and Financial Conditions*, or “The Greenbook”, its contents and use may be found on the Federal Reserve Board's website at http://www.federalreserve.gov/monetarypolicy/fomc_historical.htm. The same site also makes available archival copies of this and other FOMC briefing materials subject to a 5-year publication lag.

⁹ See Faust and Wright (2009) or Messina et al. (2015) for an alternative account of Greenbook forecasts.

Table 6

News/noise/bias test outcomes: total revisions in long-run (5 year) productivity growth.

Measure	News			Noise			Bias
	α_2	β_2	$\alpha_2 = 0, \beta_2 = 0$	α_1	β_1	$\alpha_1 = 0, \beta_1 = 0$	
GDP/EMP	0.0079 (0.0103)	−0.1151 (0.0941)	[0.1324]	−0.0158 (0.0008)	0.1421 (0.1112)	[0.0033]	−0.0029 (0.0028)
OPH: Bus.	−0.0355 (0.0063)	0.2423 (0.0628)	[0.0000]	−0.0151 (0.0073)	0.0072 (0.0670)	[0.0001]	−0.0144 (0.0032)
OPH: NFB	−0.0352 (0.0059)	0.2516 (0.0599)	[0.0000]	−0.0180 (0.0066)	0.0388 (0.0644)	[0.0000]	−0.0142 (0.0031)
OPH: MFG	−0.0317 (0.0276)	0.1922 (0.1258)	[0.0897]	0.0309 (0.0129)	−0.1303 (0.0834)	[0.0191]	0.0061 (0.0065)
MFP: MFG	0.0038 (0.0187)	0.0937 (0.1884)	[0.0271]	0.0393 (0.0151)	−0.3188 (0.1586)	[0.0045]	0.0128 (0.0037)

Notes: OPH stands for output per hour, Bus. for the Business sector, NFB for non-farm business sector, MFG manufacturing, and MFP is multifactor productivity. Newey–West HAC standard errors between brackets; p -Values of Wald (F) tests between square brackets.

Table 7

Greenbook forecast errors (Q/Q growth rates).

Horizon	Mean	St. dev.	Min	Max	# Obs
<i>1st release data</i>					
0	0	0.0044	−0.0118	0.0169	224
1	−0.0005	0.0055	−0.0176	0.0237	224
2	−0.0003	0.0059	−0.0216	0.0210	224
3	−0.0002	0.0058	−0.0201	0.0212	224
4	−0.0003	0.0057	−0.0142	0.0217	224
5	−0.0002	0.0060	−0.0157	0.0210	204
6	−0.0004	0.0055	−0.0132	0.0217	170
7	−0.0003	0.0062	−0.0140	0.0229	125
8	−0.0015	0.0057	−0.0140	0.0227	77
9	−0.0024	0.0046	−0.0140	0.0085	39
10	−0.0001	0.0061	−0.0095	0.0092	7
<i>Current vintage data</i>					
0	−0.0012	0.0062	−0.0164	0.0155	224
1	−0.0016	0.0074	−0.0212	0.0209	224
2	−0.0015	0.0074	−0.0220	0.0153	224
3	−0.0013	0.0074	−0.0206	0.0175	224
4	−0.0014	0.0071	−0.0206	0.0202	224
5	−0.0013	0.0073	−0.0213	0.0170	204
6	−0.0014	0.0066	−0.0171	0.0160	170
7	−0.0015	0.0068	−0.0179	0.0165	125
8	−0.0014	0.0071	−0.0179	0.0163	77
9	−0.0022	0.0055	−0.0179	0.0091	39
10	−0.0016	0.0082	−0.0143	0.0099	7

but that thereafter the number declines to only 125 (7) at the 7 (10) quarter horizon. These forecasts cover productivity growth from 1977Q3 to 2006Q4, a period of substantial variation in productivity growth rates. As the FOMC regularly meets eight times per year, we typically have two separate forecasts produced in each quarter. However, we make no attempt to distinguish between “early-quarter” and “late-quarter” forecasts; we would expect “early-quarter” forecasts to be somewhat less reliable and “late-quarter” forecasts to be somewhat more reliable than indicated by the results we present below.

To assess the accuracy of these forecasts, we first convert them to the implied change in the natural logarithm of productivity over the forecast horizon. We then compare the forecasts to the measured change in log productivity over the same period using both the 1st-release and the current-vintage estimates of OPH–NFB. This difference should give us an indication of whether the data revisions that we have documented are small relative to the forecast errors.¹⁰ The properties of the two sets of forecast errors are summarized in Tables 7 and 8 and Fig. 4. While we report results for all forecast horizons, due to the limited number of observations on long-horizon forecasts, we limit our discussion to forecast horizons of 0–7 quarters.

¹⁰ By comparing FOMC meeting dates with data release dates, we found that many FOMC meetings where the first period marked as a “projection” by FOMC staff (i.e. our QQ horizon forecast) was a period for which official productivity growth estimates had already been released. In such cases, however, there were typically small discrepancies between the growth rate implied by the official data series and the Greenbook projection, suggesting that the staff may have been trying to predict revisions in the official series.

Table 8

Greenbook forecast errors (cumulative growth rates).

Horizon	Mean	St. dev.	Min	Max	# Obs
<i>1st release data</i>					
0	0	0.0044	−0.0118	0.0169	224
1	−0.0005	0.0069	−0.0201	0.0270	224
2	−0.0008	0.0094	−0.0338	0.0289	224
3	−0.0010	0.0115	−0.0320	0.0298	224
4	−0.0013	0.0137	−0.0326	0.0382	224
5	−0.0024	0.0159	−0.0338	0.0464	204
6	−0.0054	0.0151	−0.0375	0.0416	170
7	−0.0074	0.0167	−0.0446	0.0472	125
8	−0.0128	0.0165	−0.0477	0.0386	77
9	−0.0182	0.0175	−0.0489	0.0056	39
10	−0.0277	0.0203	−0.0496	0.0113	7
<i>Current vintage data</i>					
0	−0.0012	0.0062	−0.0164	0.0155	224
1	−0.0027	0.0091	−0.0356	0.0196	224
2	−0.0042	0.0126	−0.0386	0.0225	224
3	−0.0055	0.0148	−0.0487	0.0289	224
4	−0.0069	0.0162	−0.0466	0.0344	224
5	−0.0086	0.0175	−0.0487	0.0394	204
6	−0.0119	0.0174	−0.0478	0.0362	170
7	−0.0142	0.0188	−0.0508	0.0295	125
8	−0.0175	0.0217	−0.0573	0.0242	77
9	−0.0219	0.0236	−0.0694	0.0236	39
10	−0.0355	0.0260	−0.0681	−0.0032	7

Fig. 4. Greenbook productivity projections, first releases and current vintage values.

Tables 7 and 8 show some important differences in forecast errors between the two outcome measures. While the forecast errors have a negative mean at almost all horizons, the mean is considerably further from zero when using current-vintage data. The standard deviation of the forecast errors are also larger, particularly at horizons 0–2 where they increase by 20–40%. These two effects combine when we calculate the root-mean-squared forecast error (RMSFE), which we show as a function of the forecast horizon in Fig. 4. The figure shows that data revision increases the apparent RMSFE by 20–45% across the eight forecast

Table 9
Decomposition of Greenbook forecast errors.

Horizon	$(y_t^{CV} - y_t^{GB})^2$	$(y_t^{CV} - y_t^{t+1})^2$	$(y_t^{t+1} - y_t^{GB})^2$	$2(y_t^{CV} - y_t^{t+1}) \cdot (y_t^{t+1} - y_t^{GB})$
0	0.399	0.387	0.191	−0.178***
1	0.896	0.658	0.480	−0.242
2	1.755	0.918	0.881	−0.044
3	2.491	1.220	1.335	−0.064
4	3.081	1.587	1.888	−0.394
5	3.800	1.737	2.565	−0.502
6	4.416	1.826	2.570	0.019
7	5.506	2.163	3.330	0.013
8	7.699	1.907	4.337	1.455*
9	10.220	1.632	6.279	2.309*
10	18.427	2.402	11.179	4.846

Notes: Numbers in columns 2–5 are multiplied by 10^4 . ***, **, * denote cross-moments significantly different from 0 at the 1%, 5%, 10% levels (HAC standard errors).

horizons shown.¹¹ We therefore conclude that data revisions appear to contribute to measured forecast errors in the Greenbook projections in an appreciable way.

To better understand the contribution of data revisions to Greenbook forecast errors, note that

$$(y_t^{CV} - y_t^{GB}) = (y_t^{CV} - y_t^{t+1}) + (y_t^{t+1} - y_t^{GB})$$

$$\therefore E(y_t^{CV} - y_t^{GB})^2 = E(y_t^{CV} - y_t^{t+1})^2 + E(y_t^{t+1} - y_t^{GB})^2 + 2 \cdot E((y_t^{CV} - y_t^{t+1}) \cdot (y_t^{t+1} - y_t^{GB}))$$

where y_t^{GB} is the Greenbook forecast for a given forecast horizon. If data revisions are pure news, then $E((y_t^{CV} - y_t^{t+1}) \cdot (y_t^{t+1} - y_t^{GB})) = 0$. A significant correlation between data revisions and 1st-release forecast errors therefore is evidence that the Board staff had some success in predicting data revisions. We investigated this using the Greenbook forecast data and vintages of cumulative Q/Q productivity (OPH NFB) growth forecasts as shown in Table 9.

We see that GB forecast errors are larger using CV, which is consistent with revisions being largely unpredictable. The cross-moments are rarely statistically different from zero. Only for the case of the nowcast do we find significant evidence that the staff's forecast seemed to anticipate some of the subsequent data revisions. We noted this in Footnote 10 above.

5. Conclusion

This paper investigated the statistical reliability of aggregate productivity estimates for the US. We explained why “recent” productivity growth estimates are much less reliable than those of other series (particularly output and employment.) The importance and robust nature of revisions reflect fundamental problems in productivity measurement rather than an unusual failure of government statisticians. The residual nature of macroeconomic productivity measurement causes productivity to be less precisely measured than output or employment. Further improving the reliability of published productivity estimates will be a major challenge.

This paper analyzed the revision of several measures of aggregate productivity growth in the US. We find that data revisions are surprisingly important, with 80% confidence intervals that are larger than the mean annual growth rate of productivity and noise/signal ratios in the range of 0.5–1.0. Revisions are important for both annual and five-year average growth rates and important revisions are made both in the first year after and long after the preliminary release. Revisions are not “well-behaved” in the sense that most of the series we examined fit neither the standard “news” nor “noise” models of measurement errors. Revision errors contribute substantially to policymakers' forecast errors at the shortest horizons and appear to increase them by 20% or more at all horizons we examine.

In a world with certainty equivalence, the accuracy of productivity estimates or forecasts would be of little consequence. However, events and economic research have increasingly stressed the role of uncertainty in macroeconomics.¹² More generally, decision makers in the public and private sectors may wish to know about the distribution of future productivity growth outcomes because they have asymmetric loss functions or perhaps because they wish to weigh several related forecasts based in part on their relative reliability. In all such situations, uncertainty due to the possibility of data revisions should be of interest to economic agents and policymakers.

We conclude that the design of macroeconomic models and policies adapted to the uncertainty surrounding key economic series, including productivity, should be a priority for economists, possibly building upon the work of [Aruoba \(2004\)](#) and [Edge et al. \(2007\)](#) on incorporating data revisions in DSGE models.

¹¹ Based on the very limited number of observations for horizons of more than 7 quarters (which also reflect the more recent Greenbook forecasts), the results in Tables 7 and 8 suggest that forecast errors continue to increase with forecast horizon.

¹² Macroeconomic theory is used to justify this in many ways, including via the zero-lower bound on interest rates, the option-value of irreversible investments, or with economic costs of financial distress following defaults. We also observe that central banks, including the Federal Reserve, explicitly consider probability density forecasts in formulating policy.

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Appendix

Let $N/S \equiv \phi$ where $\phi^2 \equiv (\mathbf{R}^Z)' \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{R}^Z$ and where $\mathbf{R}^Z$ is the $T \times 1$ vector of revisions in each element of $\mathbf{Z}$, where $\mathbf{Z}$ is also a $T \times 1$ vector and $\tilde{\mathbf{Z}}$ is the $T \times 1$ vector containing deviations of $\mathbf{Z}$ from its sample mean.

Now suppose $\mathbf{Z} = \mathbf{X} \cdot \boldsymbol{\omega}$ where $\mathbf{X}$ is a $T \times n$ matrix of variables and $\boldsymbol{\omega}$ is an unrestricted $n \times 1$ vector of weights (i.e., each element ω_i may lie anywhere on the real line). $\mathbf{R}^X$ is the conformable $T \times n$ matrix of revisions associated with each element of $\mathbf{X}$. Therefore,

$$\phi^2 \equiv (\mathbf{R}^Z)' \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{R}^Z = \boldsymbol{\omega}' \cdot (\mathbf{R}^X)' \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{R}^X \cdot \boldsymbol{\omega}.$$

Assume that

1. $(\tilde{\mathbf{X}}' \cdot \tilde{\mathbf{X}})^{-1}$ exists, where $\tilde{\mathbf{X}}$ is the $T \times 1$ vector containing deviations of $\mathbf{X}$ from its sample mean.
2. $\mathbf{C}$ exists, such that $\mathbf{C} \cdot \mathbf{C}' = (\tilde{\mathbf{X}}' \cdot \tilde{\mathbf{X}})^{-1}$ and $\mathbf{C}^{-1}$ exist.

Therefore $\phi^2 \equiv \boldsymbol{\omega}' \cdot (\mathbf{R}^X)' \cdot \mathbf{C}' \cdot (\mathbf{C}')^{-1} \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{C}^{-1} \cdot \mathbf{C} \cdot \mathbf{R}^X \cdot \boldsymbol{\omega}$, or $\phi^2 \equiv \boldsymbol{\omega}' \cdot (\mathbf{R}^X)' \cdot \mathbf{C}' \cdot [(\mathbf{C}')^{-1} \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{C}^{-1}] \cdot \mathbf{C} \cdot \mathbf{R}^X \cdot \boldsymbol{\omega} \equiv \boldsymbol{\omega}' \cdot \mathbf{A}' \cdot [\mathbf{B}] \cdot \mathbf{A} \cdot \boldsymbol{\omega}$, where $\mathbf{B} \equiv (\mathbf{C}')^{-1} \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{C}^{-1} = (\mathbf{C}')^{-1} \cdot \mathbf{C}^{-1} \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1}$ (because $\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}}$ is a scalar) $= (\tilde{\mathbf{X}}' \cdot \tilde{\mathbf{X}}) \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1}$. This is just the scaled covariance matrix of $\mathbf{X}$, where variances and covariances are scaled relative to the variance of $\mathbf{Z}$. $\mathbf{A} \equiv \mathbf{C} \cdot \mathbf{R}^X$ is the matrix N/S ratio for the series $\mathbf{X}$.

Note that the results are invariant to $|\boldsymbol{\omega}|$, since if we replace $\boldsymbol{\omega}$ everywhere with $\lambda \cdot \boldsymbol{\omega}$ for any real scalar λ , we just get $\phi^2 \equiv \lambda \cdot \boldsymbol{\omega}' \cdot (\mathbf{R}^X)' \cdot (\lambda \cdot \tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}} \cdot \lambda)^{-1} \cdot \mathbf{R}^X \cdot \boldsymbol{\omega} \cdot \lambda = \boldsymbol{\omega}' \cdot (\mathbf{R}^X)' \cdot (\tilde{\mathbf{Z}}' \cdot \tilde{\mathbf{Z}})^{-1} \cdot \mathbf{R}^X \cdot \boldsymbol{\omega}$.

In general, $\mathbf{C}$ and $\tilde{\mathbf{X}}$ will be trivial to calculate as they require only current vintage data.

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