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DECOMPOSITION

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On the correspondence between data revision and trend-cycle decomposition

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Abstract

This paper places the data revision model of Jacobs and van Norden (2011) within a class of trend-cycle decompositions relating directly to the Beveridge-Nelson decomposition. In both these approaches identifying restrictions on the covariance matrix under simple and realistic conditions may produce a smoothed estimate of the underlying series which is more volatile than the observed series.

JEL classification: C22, C53, C82

Keywords: data revisions, state-space models, Kalman filter, Kalman smoother, trend-cycle decomposition

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1 Introduction

The dynamics of measurement errors in data revisions can be cast in a state-space framework, as recently in Jacobs and van Norden (2011) (JvN henceforth). In providing this richer analysis, they employ restrictions on the covariance matrix of the state equation to identify revisions from previously unknown information (known in the data revision literature as ‘news’) from those due to a forecastable process (‘noise’).

Related parameter restrictions on the covariance matrix of the state equation are also employed in the Beveridge-Nelson (1981) trend-cycle decomposition literature (henceforth BN), see e.g. Morley (2002) and the single source of error approach of Anderson, Low and Snyder (2006). For a recent overview on parameter restrictions in state-space models see Jun et al. (forthcoming). Morley, Nelson and Zivot (2003) show that the difference between unobserved components models (UC) and Beveridge-Nelson (BN) decompositions stems from the restrictions on the correlation between innovations to trends and cycles.

Data revisions occur to an underlying series, until the final series value is reached. These final values are denoted as the ‘truth’ in JvN. They are interested in how the entry of previously unknown information and forecastable processes influences the evolution of this ‘truth’. To identify the model, shocks to the previously unknown information and the ‘truth’ are assumed to be negatively correlated. The consequence of this is that the smoothed

underlying ‘truth’ can become more volatile than the observed data. This is true even for stationary time series. Proietti (2006, p76) similarly noted that the trend may be more volatile than the observed data for BN trend-cycle decompositions. This issue is also evident in the discussion of weighting patterns and smoothing in Koopman and Harvey (2003).

All computations in this paper are done in Oxmetrics 6.20, using the SsfPack libraries.

2 The JvN model in the case of one release

For simplicity we confine our attention to the case where we observe an original data release for a variable y_t , without a subsequent revision. The only source of measurement error is the new information. Then, the measurement equation for the observed variable becomes

$$y_t = \tilde{y}_t + \nu_t = \text{Truth}_t + \text{New Information}_t. \quad (1)$$

Assuming an AR(1) process for the truth, the state equation becomes

$$\begin{bmatrix} \tilde{y}_{t+1} \\ \nu_{t+1} \end{bmatrix} = \begin{bmatrix} \rho & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \tilde{y}_t \\ \nu_t \end{bmatrix} + \begin{bmatrix} \sigma_e & \sigma_\nu \\ 0 & -\sigma_\nu \end{bmatrix} \begin{bmatrix} \eta_{et} \\ \eta_{\nu t} \end{bmatrix}, \quad (2)$$

where $\boldsymbol{\eta}_t \sim N(0, \mathbf{I}_2)$. Note that

$$\begin{bmatrix} \sigma_e & \sigma_\nu \\ 0 & -\sigma_\nu \end{bmatrix} \begin{bmatrix} \sigma_e & \sigma_\nu \\ 0 & -\sigma_\nu \end{bmatrix}' = \begin{bmatrix} \sigma_e^2 + \sigma_\nu^2 & -\sigma_\nu^2 \\ -\sigma_\nu^2 & \sigma_\nu^2 \end{bmatrix} = \sigma_\nu^2 \begin{bmatrix} \frac{\sigma_e^2}{\sigma_\nu^2} + 1 & -1 \\ -1 & 1 \end{bmatrix},$$

so the truth and new information shocks (given by η_{et} and $\eta_{\nu t}$) are negatively correlated, and the ratio $\frac{\sigma_e^2}{\sigma_\nu^2}$ plays an important role. If the ratio becomes large shocks to the truth dominate; if it becomes small, the covariance matrix becomes $\sigma_\nu^2 \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$. This is precisely the covariance matrix of the state space representation of the Beveridge-Nelson decomposition; Morley, Nelson and Zivot (2003).

3 Filtering and smoothing

Figure 1 shows the smoothed and filtered truth together with the standardized simulated series from the model of Section 2 for $(\rho, \sigma_e, \sigma_\nu) = (0.25, 0.5, 0.5)$. We observe that the filtered truth is exactly the same as the simulated series, whereas the smoothed truth is very close to the observed series.

[Figure 1 about here.]

In Figure 2 we assume that disturbance of the new information is ten times larger than the disturbance of the truth $(\rho, \sigma_e, \sigma_\nu = 0.25, 0.5, 2.5)$. The filtered truth is still exactly the same as the simulated series, but now the smoothed truth is much more volatile than the simulated series.

[Figure 2 about here.]

The negative correlation between shocks to the truth and new information via data revisions implies that the volatility of the smoothed series is higher than the volatility of the simulated series. The variability of the smoothed series is increased when future measurement errors (which in this case pertain to new information) are negatively correlated with the truth disturbances.

Figure 3 shows the sensitivity of the variances of the smoothed truth and the filtered truth as the ratio $\frac{\sigma_s^2}{\sigma_v^2}$ varies. We let the size of both shocks vary from 0.05 to 5, and hence the ratio $\frac{\sigma_s^2}{\sigma_v^2}$ ranges from 1 : 10000 to 10000 : 1. The top panel shows that when the shock to new information is much larger than the shock to truth, the smoothed truth is more volatile and the variance dramatically increases with the shock to new information. However, changes in the variance of the filtered truth are barely visible in the bottom panel.

[Figure 3 about here.]

The estimation results reported in JvN are based on data with four revisions. In all cases where new information shocks enter the state equation for the truth in the JvN data revision frameworks, the correlation between truth and new information shocks is negative. In addition, JvN find that shocks to new information are at least five times as large as those to alternative sources of shocks to the measurement error. Consequently, smoothed output growth is much more volatile than observed output growth. The existence of new information in the revision process of output growth suggests that

statistical agencies act to smooth the ‘noisy’ true output growth series. It also sheds new light on the data reconciliation debate initiated by Stone, Champernowne and Meade (1942) on the choice of the better estimate of the growth rate of “true” output. For a recent contribution on the US see Fixler, Greenaway-McGrevy and Grimm (2011).

4 Conclusion

The JvN data revision model is related to trend-cycle decompositions in a way made obvious by the state space representation. Identification is achieved through restrictions on the variance-covariance matrix of the state equation, where the disturbances of the unobserved components are negatively correlated. This can result in the proposed ‘truth’ underlying the observed variable being more volatile than the observed data series.

These observations also hold when there are multiple revisions to a data series. The volatile nature of many real time data revisions does not therefore imply these data are non-informative, nor do our results support the tempting use of filtered data in place of such series. Future research will establish whether these properties apply to further economic series beyond the output data investigated in JvN.

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Figure 1: Smoothed and filtered truth and simulated series, $(\rho, \sigma_e, \sigma_\nu) = (0.25, 0.5, 0.5)$

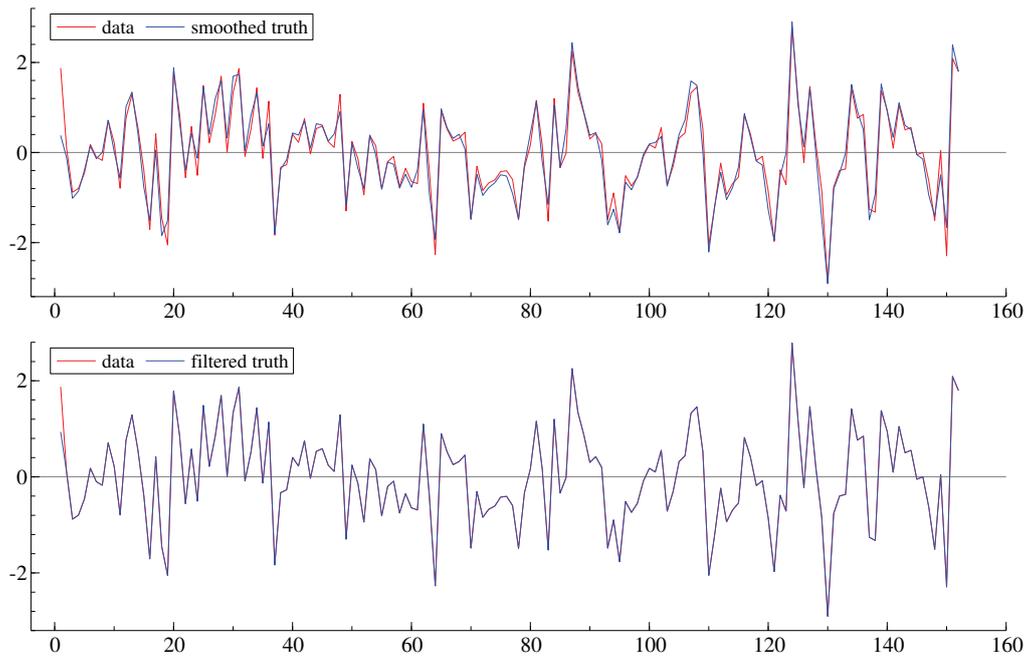


Figure 2: Smoothed and filtered truth and simulated series, $(\rho, \sigma_e, \sigma_\nu) = (0.25, 0.5, 2.5)$

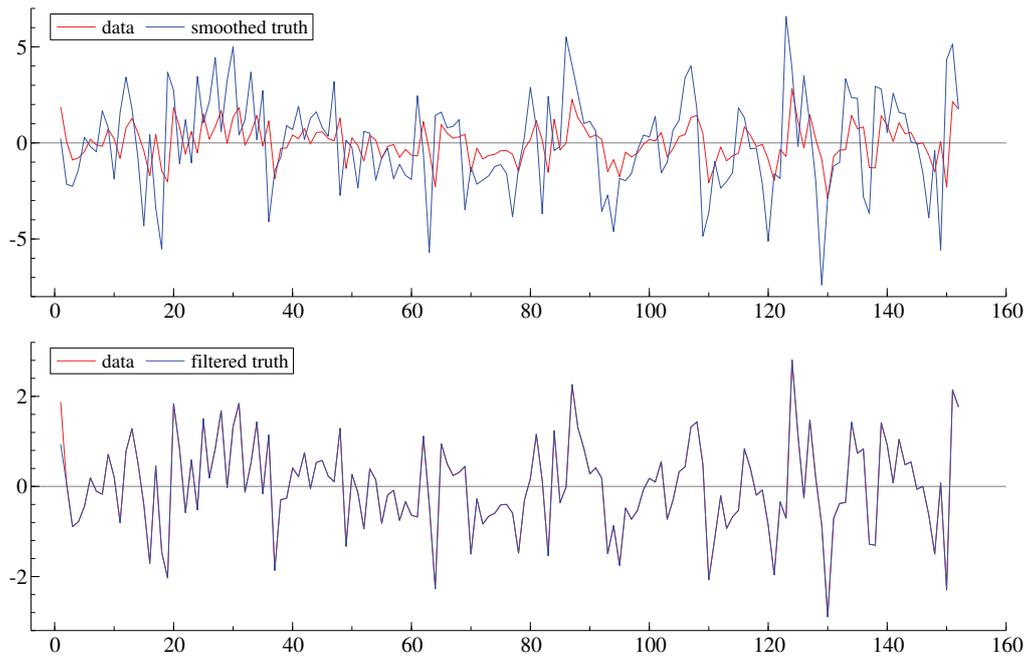


Figure 3: Sensitivity of smoothed and filtered truth and simulated series, to

