Explaining Business Cycles: News Versus Data Revisions

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Outline of Paper

- Effects of 'news' as an explanation of business cycles
- Estimates of news effects
- Informational consistency principle, and the role of imperfect information - data revisions - as a source of news
- How does one test news against the effects of data revisions?
- Test results
Beaudry and Portier (2006) introduced the idea of news - information on shocks that arrives several periods in advance of the shocks’ effect - using VARs empirically.

Fujiwara et al (2011) find that news, which in principle enables agents to improve forward-looking expectations, improved marginal likelihood for US data but not Japanese data.

Schmitt-Grohe and Uribe (2010) in earlier versions also found marginal likelihood was improved, but in the current version omit this, focusing on variance decomposition.

Forni et al (2011) find no improvement.

Background Literature on Imperfect and Heterogeneous Information

- Collard and Dellas (2006) show that imperfect information can introduce endogenous persistence into IRFs because dynamics are more drawn out.

- Collard et al (2009) and Levine et al (2010) have estimated DSGE models assuming agents have the same imperfect information sets as econometricians (the informational consistency principle), and found that marginal likelihoods improve.

- Lorenzoni (2009), Graham and Wright (2010) and Nimark (2008), assume heterogeneous shocks, and are better able to match co-movements of key variables.
Background Literature on Data Revisions

- Studies on real-time data initiated by Croushore.
- These have influenced both forecasting and policy design.
- Fernandez and Swanson (2009), de Antonio Liedo and Carstensen (2006), de Castro et al. (2011) and Clements and Galvao (2011) have subsequently studied the real-time data.
- They have shown that there is sufficient information in the correlation in errors from one revision to the next for agents to forecast some proportion of the next periods update on the data.
- In other words, there is news that is contained in the data revisions that may be an alternative to the news about future shocks.
The RE Model: Linearized Model

\[ y_t = c_y c_t + (1 - c_y) g_t \]  where \( c_y = \frac{C}{Y} \)

\[ E_t \mu^C_{t+1} = \mu^C_t - (r_t - E_t \pi_{t+1}) \]

\[ \pi_t = \beta E_t \pi_{t+1} + \frac{(1 - \beta \xi)(1 - \xi)}{1 + \beta \gamma \xi} (mc_t + ms_t) \]

where marginal utility, \( \mu^C_t \), and marginal costs, \( mc_t \), are defined by

\[ \mu^C_t = \frac{(1 - \varphi)(1 - \sigma) - 1}{1 - h_c} (c_t - h_c c_{t-1}) - \frac{\varphi(1 - \sigma)L}{1 - L} l_t \]

\[ mc_t = w_t - p_t - a_t + (1 - \alpha) l_t \]

\[ w_t - p_t = \mu^L_t - \mu^C_t \]

\[ y_t = a_t + \alpha l_t \]

\[ \mu^L_t = \frac{1}{1 - h_c} (c_t - h_c c_{t-1}) + \frac{L}{1 - L} l_t + \mu^C_t \]
Shock Processes and Taylor Rule

\[ g_{t+1} = \rho g_t + \epsilon_{g,t+1} \]
\[ a_{t+1} = \rho a_t + \epsilon_{a,t+1} \]
\[ msper_{t+1} = \rho_{ms} msper_t + \epsilon_{msper,t+1} \]
\[ ms_t = msper_t + \epsilon_{msper,t} \]
\[ r_t = \rho r_{t-1} + (1 - \rho_r)[\theta_{\pi} \pi_t + \theta_{y} y_t] + \epsilon_{e,t} \]

where we have decomposed the price mark-up shock \( ms_t \) into persistent and transient components, \( msper_t \) and \( \epsilon_{msper,t} \) respectively.
Shocks are modelled as

\[ a_t = \rho a_{t-1} + \mu_t \]
\[ \mu_t = \epsilon_{x,t}^0 + \epsilon_{x,t-1}^1 + \epsilon_{x,t-2}^2 + \epsilon_{x,t-3}^3 \]

Thus agents can forecast

\[ E_t \mu_{t+1} = \epsilon_{x,t}^1 + \epsilon_{x,t-1}^2 + \epsilon_{x,t-3}^3 \]
\[ E_t \mu_{t+2} = \epsilon_{x,t}^2 + \epsilon_{x,t-1}^3 \]
\[ E_t \mu_{t+3} = \epsilon_{x,t}^3 \]
\[ E_t \mu_{t+m} = 0; \quad m \geq 4 \]
Imperfect Information

- Real-time observations incorporate errors, and data is collected with a lag as well.
- US GDP data is rarely revised beyond 3 quarters.
- Price data is fairly accurate in the first period it is collected, so for simplicity we assume no errors.
- There are correlations in real-time GDP, modelled below:

\[
\begin{align*}
    y_{t-1}^{\text{obs}} &= y_{t-1} + \epsilon_t^0 + \epsilon_t^1 \\
    y_{t-2}^{\text{obs}} &= y_{t-2} + \alpha_y \epsilon_{t-1}^1; \quad \alpha_y \in [0, 1] \\
    y_{t-3}^{\text{obs}} &= y_{t-3} \\
    \pi_{t-1}^{\text{obs}} &= \pi_{t-1}
\end{align*}
\]
Previous Imperfect Information Estimation

- Levine et al (2010) use historical (not real-time data) to compare standard estimation procedures with informationally consistent procedures.
- Standard estimation: Agents have full information about all shocks, while econometricians only have information on GDP, inflation, consumption etc - asymmetric info (AI)
- Informationally consistent estimation: agents have the same imperfect information set as econometricians - symmetric imperfect info (II).
- Typical results were:

<table>
<thead>
<tr>
<th>Model</th>
<th>Information</th>
<th>Log Data Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>AI, no measurement error</td>
<td>-99.48</td>
</tr>
<tr>
<td>II</td>
<td>II, no measurement error</td>
<td>-96.48</td>
</tr>
</tbody>
</table>
Results for Standard Comparison of AR(1) vs News Shocks

- These assume asymmetric info (AI) - agents have full information, whereas econometricians have historical information on GDP, inflation and interest rates, all without error
- Two scenarios:
  1. AR(1) process for technology shocks
  2. News process for technology shocks

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<tbody>
<tr>
<td>I</td>
<td>AR(1)</td>
<td>AI, no measurement error</td>
<td>-239.3</td>
</tr>
<tr>
<td>II</td>
<td>News</td>
<td>AI, no measurement error</td>
<td>-240.6</td>
</tr>
</tbody>
</table>

- No significant improvement for news
Results for Imperfect Information Compared with Previous Assumptions, Using Real-Time Data

- This time we compare the log marginal likelihoods, using real-time revised data, of three scenarios:
  1. AR(1) process for technology shocks, under AI
  2. News process for technology shocks, under AI
  3. AR(1) process for technology shocks, under symmetric II

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</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>AR(1)</td>
<td>AI with revisions</td>
<td>-366.8</td>
</tr>
<tr>
<td>II</td>
<td>News</td>
<td>AI with revisions</td>
<td>-371.0</td>
</tr>
<tr>
<td>III</td>
<td>AR(1)</td>
<td>II with revisions</td>
<td>-360.3</td>
</tr>
</tbody>
</table>

- Here, the effect of news is to lower the marginal data density, but the effect of imperfect information is to increase it.
Conclusions

- Real-time data appears to play a similar role to news shocks, but outperforms the latter, at least for a stripped-down DSGE model.
- Collard and Dellas (2006) and Levine et al (2010) showed that imperfect information on the part of agents can generate longer drawn out cycles.
- Correlations of measurement error across periods allow agents to anticipate part of next periods data revision, and thereby to improve estimates of the size of current period shocks and also subsequent shocks.
- These explain why real-time data under symmetric imperfect information performs so well.