Understanding Uncertainty Shocks

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1Disclaimer: The views expressed herein are those of the authors and do not necessarily reflect the position of the Board of Governors of the Federal Reserve or the Federal Reserve System
Introduction

- What shocks drive business cycles?
  What shocks cause asset returns to fluctuate?

- Recent advance in this quest: uncertainty shocks.

- Many papers are exploring the effects of uncertainty shocks.

  **Finance**: Di Tella (2013), Gorurio and Michaux (2012)

- Where do these shocks come from? How should we measure them?
Where Do Uncertainty Shocks Come From?

- Uncertainty: Stdev of a forecast error conditional on $\mathcal{I}_{it}$.

$$U_{it}^{(h)} = \sqrt{E \left[ (y_{t+h} - E(y_{t+h} | \mathcal{I}_{it}))^2 \right | \mathcal{I}_{it}]}$$

- Answer 1: **Uncertainty shocks come from volatility shocks.**

  Suppose $\mathcal{I}_{it} = \{\text{model } \mathcal{M}, \text{parameters } \theta, \text{history } y^t\}$. Example:

  If $y_{t+1} = \mu + b_1 y_t + b_2 z_t + e_{t+1}$ then $U_t = V_t = std(e_t)$

  - Volatility shocks are shocks to $std(e_t)$. Where do they come from?
  - How does everyone know immediately that $std(e_t)$ changed?
  - If we want to understand and measure uncertainty, does rational expectations econometrics make sense?
Where Do Uncertainty Shocks Come From?

- Uncertainty: Stdev of a forecast error conditional on $I_{it}$.

$$U_{it}^{(h)} = \sqrt{E \left[ (y_{t+h} - E(y_{t+h}|I_{it}))^2 |I_{it}\right]}$$

- Answer 1: Uncertainty shocks come from volatility shocks.
- Answer 2: **Uncertainty shocks come from model uncertainty.**

Suppose $I_{it} = \text{model } M$, history $y^t$. Volatility is constant.

2 mechanisms move $U_t$:
  - Unexpected events $\rightarrow$ parameter revisions.
  - Learning about skewness changes the probability of “black swans.”

**Message:** Rational expectations econometrics misses many uncertainty shocks.
A (homoskedastic) continuous hidden state model

$$y_t = \alpha + S_t + \sigma \varepsilon_t$$

$$S_t = \rho S_{t-1} + \sigma^S \xi_t$$

where $\varepsilon_t$ and $\xi_t \sim iid \ N(0, 1)$. Let $\theta = \{\alpha, \rho, \sigma, \sigma^S\}$.

At every time $t$, $\mathcal{I}_t = \{M, y^t\}$. $y^t = \text{real-time GDP growth 1968-}t$.

A forecast is:

$$E(y_{t+1}|M, y^t) = \int y_{t+1} f(y_{t+1}|M, y^t) dy_{t+1}$$

where

$$f(y_{t+1}|M, y^t) = \int \int f(y_{t+1}|S_{t+1}, \theta, M) f(S_{t+1}|\theta, M, y^t) f(\theta|M, y^t) dS_{t+1} d\theta$$

Start with priors and update with Bayes’ law.

Compute $U_t \equiv \sqrt{\text{Var}(y_{t+1}|M, y^t)}$ at each date.
Uncertainty shocks with constant volatility!
Linear Model Results

Uncertainty shocks with constant volatility!

Why? \( \text{Surprise}_t = \frac{|y_t - E(y_t|y_{t-1})|}{U_{t-1}} \).

But results expose 3 problems: 1) Shocks are small, 2) uncertainty is not counter-cyclical, 3) Forecasts don’t resemble professional forecasts (SPF mean is lower than \( \bar{y}_t \) by 0.44%).
A Nonlinear Forecasting Model

How to compute? Change of measure: Transform data to make it normal. Example:

\[ y_t = c - b \exp(-X_t) \]

where \( X_t \) follows same continuous hidden state model as before.

We estimate by converting our data: \( X_t = -\log((c - y_t)/b) \). Then, use previous tools for normal-linear processes to form \( f(X_t|X_{t-1}, M) \).

Use the change of measure to calculate \( E[y_t|y_{t-1}] \) and \( U_t \).

NL model: \( c/b = 24.9 \) is known. It fits skewness of ’47-’68 data. Learn \( c \): Update skewness each period and re-calibrate \( b, c \).
Nonlinear Model Results
Nonlinear Model Results

BlackSwan_t = Prob(y_t < -6.8%). 1 in 100 year event if y_t ∼ N(μ, σ^2).

Results raise these questions

1. How does nonlinearity affect uncertainty? Why counter-cyclical?
2. Why does the model explain professional forecasters’ bias?
3. How does this interact with forecast dispersion?
Concavity is key to counter-cyclical uncertainty. When estimated, it arises naturally because GDP growth is negatively skewed. Also, many theories explain why bad times can be really bad.
Q2: Why Does Nonlinearity Generate Forecast “Bias”?  

Facts: Avg GDP growth = 2.7%. Average SPF = 2.2%.  
In the model: Average $E[y_{t+1}|I_t] = 2.2\%$.  

![Diagram showing the relationship between GDP growth and state, illustrating the Jensen effect.](image-url)
Q2: Why Does Nonlinearity Generate Forecast “Bias”? 

Facts: Avg GDP growth = 2.7%. Average SPF = 2.2%. 
In the model: Average $E[y_{t+1}|I_t] = 2.2\%$. 

![Diagram showing the relationship between GDP growth and state, highlighting the difference between the expected values under different conditions and the additional Jensen effect from model uncertainty.]

- $E[y_{t+1}|y_t, M, \theta]$ 
- $E[y_{t+1}|y_t]$ 
- $E[X_{t+1}|X^t]$
- Additional Jensen effect from model uncertainty 
- Forecaster believes $f(X_{t+1}|X^t)$
Nonlinear Forecasting with Forecast Dispersion

- New research in progress: Might a nonlinear model explain the statistical relationship between forecast dispersion and uncertainty?
- Finding: relationship between dispersion and macro uncertainty exists, even after controlling for recessions or GDP growth.
- A potential explanation:

```
GDP Growth (y)
forecast dispersion
information dispersion
```

- Helps us think about this link between micro and macro uncertainty.
Conclusions

- If agents know the data generating process, $U_t = VOL_t$. Uncertainty shocks come from volatility shocks.

- But if an econometrician can’t determine the true model, how do agents know it?

- When we allow agents to learn about models, two new sources of uncertainty shocks arise:
  - Parameter revisions after unusual events.
  - Learning about higher moments of distribution.

- Rational expectations econometrics has produced many insights. But assuming that agents know the true model of the economy ignores important sources of economic uncertainty.
Conclusion

I'm uncertain about the uncertainty of the economy. This, I am certain of...
Results for 5 Models

- Same model as before except, at each date $t$, agents re-compute $c$ to match the skewness of GDP data 1947:Q4-$t$.

<table>
<thead>
<tr>
<th>Moments</th>
<th>Data</th>
<th>$\theta$ known</th>
<th>L Model</th>
<th>NL Model</th>
<th>learn $c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean forecast</td>
<td>2.24%</td>
<td>2.68%</td>
<td>3.06%</td>
<td>2.24%</td>
<td>2.21%</td>
</tr>
<tr>
<td>Mean $</td>
<td>FErr</td>
<td>$</td>
<td>2.20%</td>
<td>2.38%</td>
<td>2.31%</td>
</tr>
<tr>
<td>Mean $U_t$</td>
<td>–</td>
<td>2.91%</td>
<td>3.40%</td>
<td>5.79%</td>
<td>7.66%</td>
</tr>
<tr>
<td>Stdev $U_t$</td>
<td>–</td>
<td>0</td>
<td>0.20%</td>
<td><strong>0.71%</strong></td>
<td><strong>1.60%</strong></td>
</tr>
<tr>
<td>Correl($\tilde{U}_t$,GDP)</td>
<td>–</td>
<td>0</td>
<td>13%</td>
<td>-90%</td>
<td>-34%</td>
</tr>
</tbody>
</table>

- Uncertainty shocks are more than twice as large!
- But they are also much less counter-cyclical.
  Counteracting force: High growth raises the mean, increases negative skewness, reduces $\hat{c}$ and increases uncertainty.
## Full Results: Uncertainty and Volatility

<table>
<thead>
<tr>
<th>model</th>
<th>linear (1)</th>
<th>nonlinear (2)</th>
<th>learn c (3)</th>
<th>signals (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>$U_t$</td>
<td>3.38%</td>
<td>5.79%</td>
<td>7.65%</td>
</tr>
<tr>
<td></td>
<td>$V_t$</td>
<td>2.91%</td>
<td>6.82%</td>
<td>6.82%</td>
</tr>
<tr>
<td>Std deviation</td>
<td>$U_t$</td>
<td>0.21%</td>
<td>0.71%</td>
<td>1.60%</td>
</tr>
<tr>
<td></td>
<td>$V_t$</td>
<td>0%</td>
<td>0.37%</td>
<td>0.37%</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>$U_t$</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>$V_t$</td>
<td>0</td>
<td>0.47</td>
<td>0.47</td>
</tr>
<tr>
<td>detrended data moments</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std deviation</td>
<td>$\tilde{U}_t$</td>
<td>2.14%</td>
<td>3.18%</td>
<td>7.18%</td>
</tr>
<tr>
<td></td>
<td>$\tilde{V}_t$</td>
<td>0%</td>
<td>5.11%</td>
<td>5.11%</td>
</tr>
<tr>
<td>Corr($\tilde{U}_t$, $y_t$)</td>
<td>0.28</td>
<td>-0.90</td>
<td>-0.34</td>
<td>0.27</td>
</tr>
<tr>
<td>Corr($\tilde{V}_t$, $y_t$)</td>
<td>0</td>
<td>-0.92</td>
<td>-0.92</td>
<td>0</td>
</tr>
<tr>
<td>Corr($\tilde{U}<em>t$, $y</em>{t+1}$)</td>
<td>0.24</td>
<td>-0.22</td>
<td>-0.10</td>
<td>0.24</td>
</tr>
<tr>
<td>Corr($\tilde{V}<em>t$, $y</em>{t+1}$)</td>
<td>0</td>
<td>-0.23</td>
<td>-0.23</td>
<td>0</td>
</tr>
</tbody>
</table>
RGDP growth and forecasted growth
Parameter Estimates from Normal Shocks Model

![Graph showing parameter estimates from 1970 to 2010 for different models. The graph displays the evolution of parameters $\alpha$, $\rho$, $\sigma$, and $\sigma^s$ over time, with trends indicating how these parameters change from 1970 to 2010.]
How Does $U_t$ Compare with Common Measures?

Uncertainty Proxy Variables

<table>
<thead>
<tr>
<th>Year</th>
<th>GARCH vol</th>
<th>Forecast MSE</th>
<th>Forecast disp</th>
<th>VIX</th>
<th>BBD policy unc</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
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<tr>
<td>1975</td>
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<td>1980</td>
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<td>1985</td>
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<tr>
<td>1990</td>
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<td>1995</td>
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<td>2000</td>
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<tr>
<td>2005</td>
<td></td>
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<tr>
<td>2010</td>
<td></td>
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</tr>
</tbody>
</table>

Corr $U_t$: GARCH 7%, MSE -3%, Disp 20%, VIX 36%, BBD 21%.
Are uncertainty shocks volatility shocks?

\[
VOL_{it} = \sqrt{E \left[ (y_{t+1} - E(y_{t+1}|y_t^i, \theta, \mathcal{M}))^2 | y_t^i, \theta, \mathcal{M} \right]}
\]

\[
U_{it}^{(h)} = \sqrt{E \left[ (y_{t+h} - E(y_{t+h}|\mathcal{I}_it))^2 | \mathcal{I}_it \right]}
\]

\[
MSE_{t+1} = \sqrt{\frac{1}{N} \sum_i [y_{t+1} - E(y_{t+1}|\mathcal{I}_it)]^2}
\]

- If many forecasters, with indep errors, then \(MSE_{t+1} = U_t\).

<table>
<thead>
<tr>
<th>Proxy</th>
<th>Mean</th>
<th>Coeff Var</th>
<th>Autocorrel</th>
<th>Correl w/GDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>2.64</td>
<td>0.58</td>
<td>0.48</td>
<td>0.04</td>
</tr>
<tr>
<td>GARCH vol</td>
<td>3.65</td>
<td>0.37</td>
<td>0.9</td>
<td>0.06</td>
</tr>
</tbody>
</table>

- Series differ greatly! Small sample and error correlation do not fully explain the difference (see paper).

*Uncertainty shocks do not seem to be fully explained by volatility shocks.*
Comparison with proxies (detrended) uncertainty

Uncertainty Proxy Variables, Detrended

- GARCH vol
- Forecast MSE
- Forecast disp
- VIX
- VIX
- BBD policy unc


−1.5
−1
−0.5
0
0.5
1
1.5

GARCH vol
Forecast MSE
Forecast disp
VIX
BBD policy unc
Considering Policy Uncertainty

- Could GDP growth uncertainty come from uncertainty about future fiscal or monetary policy?
- Maybe, but policy uncertainty may also come from model uncertainty.
- If many forecasters, with indep errors, then $MSE_{t+1} = U_t$. If $\{\theta, \mathcal{M}\}$ known, then $U_t = VOL_t$.

\[
U_{it}^{(h)} = \sqrt{E \left[ (y_{t+h} - E(y_{t+h}|I_{it}))^2 |I_{it} \right]}
\]

\[
MSE_{t+1} = \sqrt{\frac{1}{N} \sum_i [y_{t+1} - E(y_{t+1}|I_{it})]^2}
\]

\[
VOL_{it} = \sqrt{E \left[ (y_{t+1} - E(y_{t+1}|y_i^t, \theta, \mathcal{M}))^2 |y_i^t, \theta, \mathcal{M} \right]}
\]
Considering Policy Uncertainty (2)

- If policy models and parameters are known, then we should see \( \text{MSE}_{t+1} \approx \text{VOL}_t \).

- Do these two series look similar? No.

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>coeff var</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fed Gov’t Spending</td>
<td>6.36</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>5.9</td>
<td>0.01</td>
</tr>
<tr>
<td>Interest Rate</td>
<td>1</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>0.47</td>
<td>0.65</td>
</tr>
</tbody>
</table>

- Small sample and error correlation do not fully explain the difference (see paper for simulation experiments).

If policy volatility does not fluctuate much, perhaps policy uncertainty also comes from model uncertainty.
Isn’t Forecast Dispersion a ”Model-free” Uncertainty Measure?

A general orthogonal decomposition:

\[ y_{t+1} = E\left(y_{t+1}|I_{it}\right) + \eta_t + \epsilon_{it} \]

Then, uncertainty and forecast dispersion are

\[ U_{it}^2 = E\left[(\eta_t + \epsilon_{it})^2 |I_{it}\right] = \text{Var}(\eta_t | I_{it}) + \text{Var}(\epsilon_{it} | I_{it}) \]

\[ D_t^2 = \frac{1}{N} \sum_i \left( E\left(y_{t+1}|I_{it}\right) - \overline{E}_t \right)^2 = \frac{1}{N} \sum_i \text{Var}(\epsilon_{it} | I_{it}) \]

Dispersion measures uncertainty with the following model assumptions:

1. \( \text{Var}(\eta_t | I_{it}) = 0 \)
2. \( \text{Var}(\epsilon_{it} | I_{it}) = \text{Var}(\epsilon_{jt} | I_{jt}) \) for all \( i, j, t \).