Understanding Uncertainty Shocks

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[1]Disclaimer: 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.
  Macro: Bloom (2009), Bloom, Floetotto, Jaimovich, Sapora-Eksten, and Terry (2012), Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez (2011), Nakamura, Sergeyev, and Steinsson (2012), Christiano, Motto and Rostagno (2012), Arellano, Bai and Kehoe (2012), Basu and Bundick (2012), Bidder and Smith (2012).

  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 $\mathcal{I}_{it}$.

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

- Answer 1: **Uncertainty shocks come from volatility shocks.** Suppose $\mathcal{I}_{it} = \{\text{model } \mathcal{M}, \text{ parameters } \theta, \text{ history } y^t\}$. Example:

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

  - 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?

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

  as in Cogley & Sargent (2005), Johannes, Lochstoer, & Mou (2011), Hansen (2007).

  Suppose $\mathcal{I}_{it}$ = model $\mathcal{M}$, 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.

Linear Forecasting Model with Parameter Uncertainty

- A (homoskedastic) continuous hidden state model

$$\begin{aligned} y_t &= \alpha + S_t + \sigma\varepsilon_t \\ S_t &= \rho S_{t-1} + \sigma^S \xi_t \end{aligned}$$

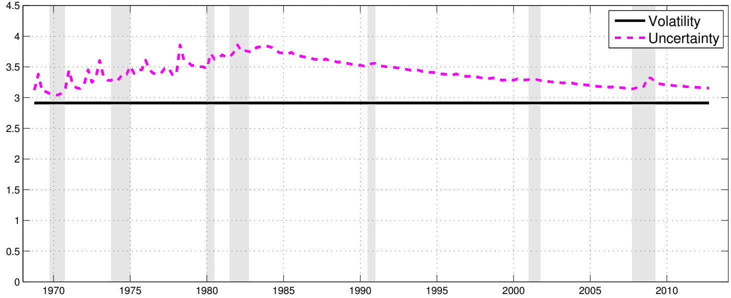
  where ε_t and $\xi_t \sim iid\ N(0,1)$. Let $\theta = \{\alpha, \rho, \sigma, \sigma^S\}$.

- At every time t, $\mathcal{I}_t = \{\mathcal{M}, y^t\}$. $y^t =$ real-time GDP growth 1968-t.
- A forecast is: $E(y_{t+1}|\mathcal{M}, y^t) = \int y_{t+1} f\left(y_{t+1}|\mathcal{M}, y^t\right) dy_{t+1}$ where

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

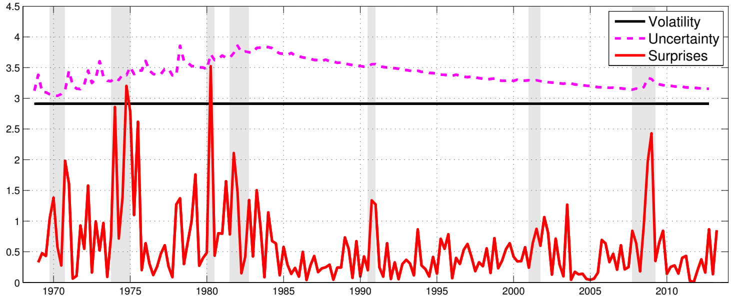
- Start with priors and update with Bayes' law.
- Compute $U_t \equiv \sqrt{Var(y_{t+1}|\mathcal{M}, y^t)}$ at each date.

Linear Model Results



Uncertainty shocks with contant volatility!

Linear Model Results



Uncertainty shocks with constant volatility!

Why? $Surprise_t = \frac{|y_t - E(y_t|y^{t-1})|}{U_{t-1}}$.

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:

$$y_t = c - b\exp(-X_t)$$

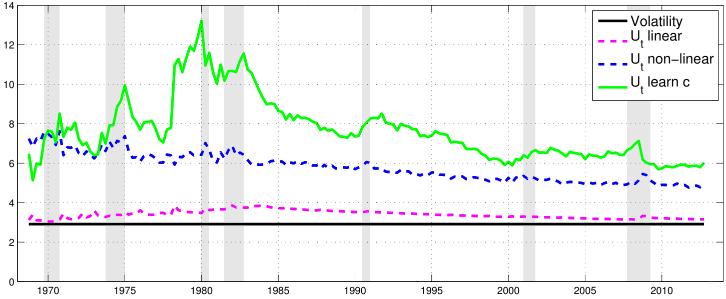
  where X_t follows same continuous hidden state model as before.

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

- 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



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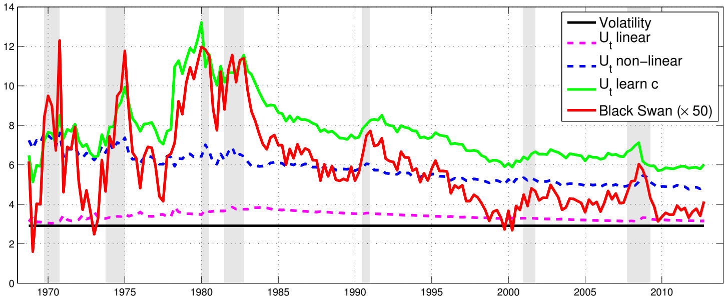
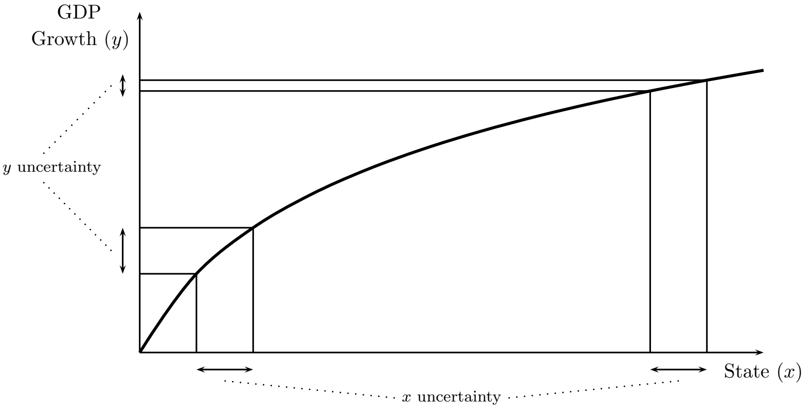


$BlackSwan_t = Prob(y_t < -6.8\%)$. 1 in 100 year event if $y_t \sim N(\mu, \sigma^2)$.

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?

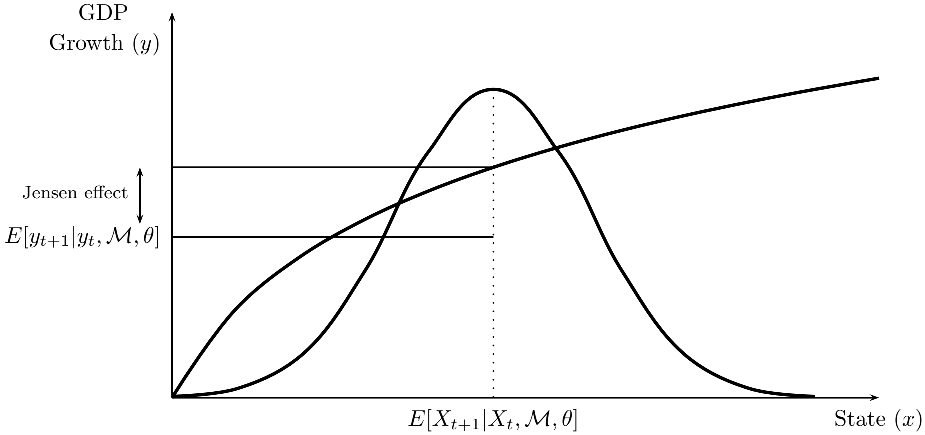
Q1: How Does Nonlinearity Affect Uncertainty?



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 $E[y_{t+1}|\mathcal{I}_t] = 2.2\%$.



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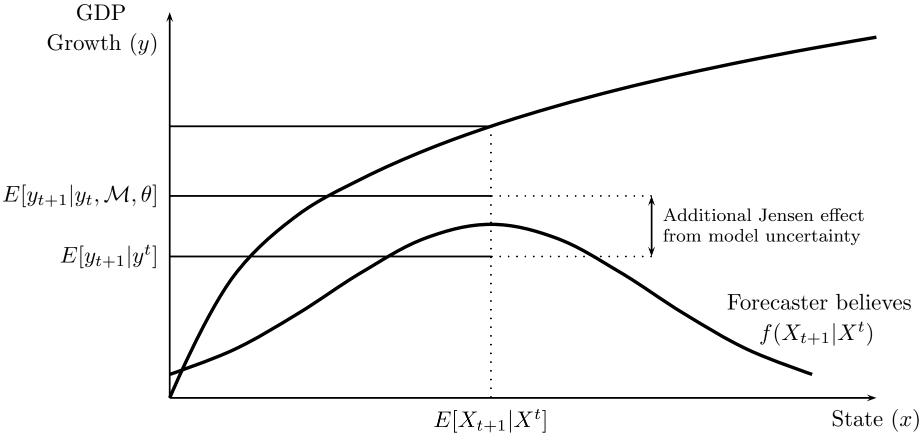
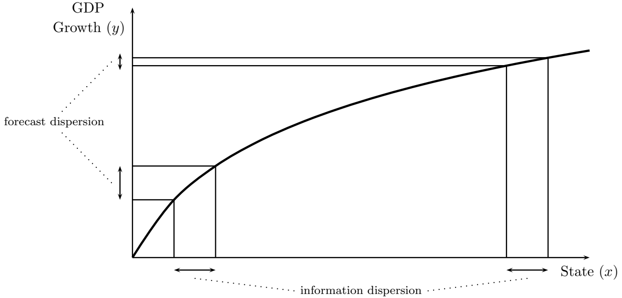


Nonlinear Forecasting with Forecast Dispersion

- 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:



  - 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...
ALDINGER
ple's Weekly World
6/2008

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.

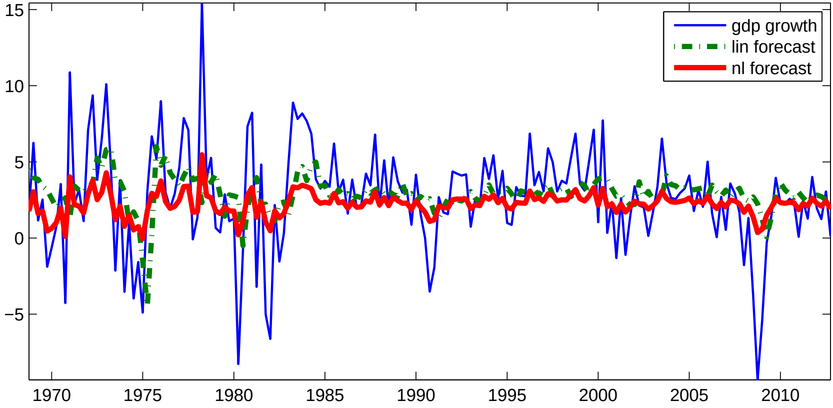
Moments	Data	θ known	L Model	NL Model	learn c
Mean forecast	2.24%	2.68%	3.06%	2.24%	2.21%
Mean $\|FErr\|$	2.20%	2.38%	2.31%	2.35%	2.40%
Mean U_t	–	2.91%	3.40%	5.79%	7.66%
Stdev U_t	–	0	0.20%	**0.71%**	**1.60%**
Correl($\tilde{U}_t$,GDP)	–	0	13%	-90%	-34%

- 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.

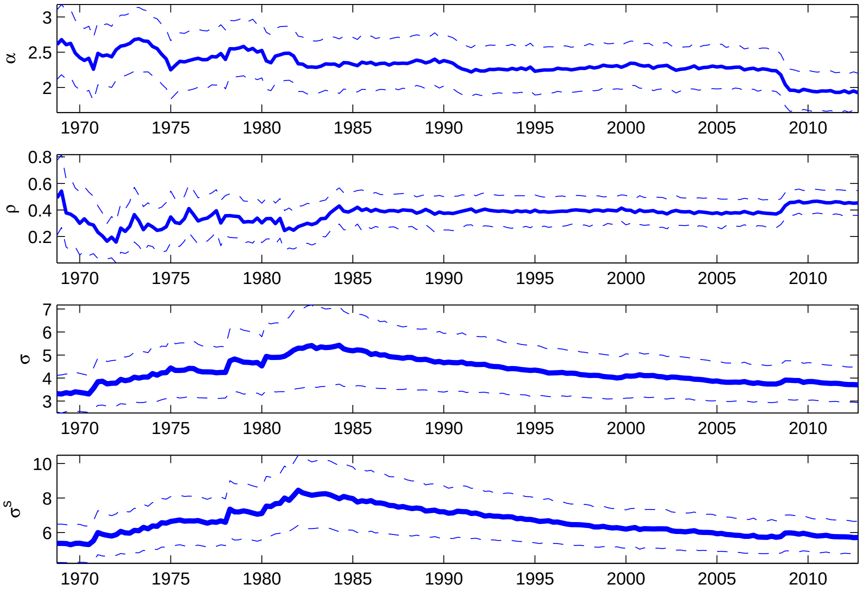
Full Results: Uncertainty and Volatility

model		linear (1)	nonlinear (2)	learn c (3)	signals (4)
Mean	U_t	3.38%	5.79%	7.65%	2.11%
	V_t	2.91%	6.82%	6.82%	2.73%
Std deviation	U_t	0.21%	0.71%	1.60%	0.05%
	V_t	0%	0.37%	0.37%	0.21%
Autocorrelation	U_t	0.95	0.95	0.95	0.95
	V_t	0	0.47	0.47	0
detrended data moments					
Std deviation	$\tilde{U}_t$	2.14%	3.18%	7.18%	0.82%
	$\tilde{V}_t$	0%	5.11%	5.11%	0%
Corr($\tilde{U}_t$, y_t)		0.28	-0.90	-0.34	0.27
Corr($\tilde{V}_t$, y_t)		0	-0.92	-0.92	0
Corr($\tilde{U}_t$, y_{t+1})		0.24	-0.22	-0.10	0.24
Corr($\tilde{V}_t$, y_{t+1})		0	-0.23	-0.23	0

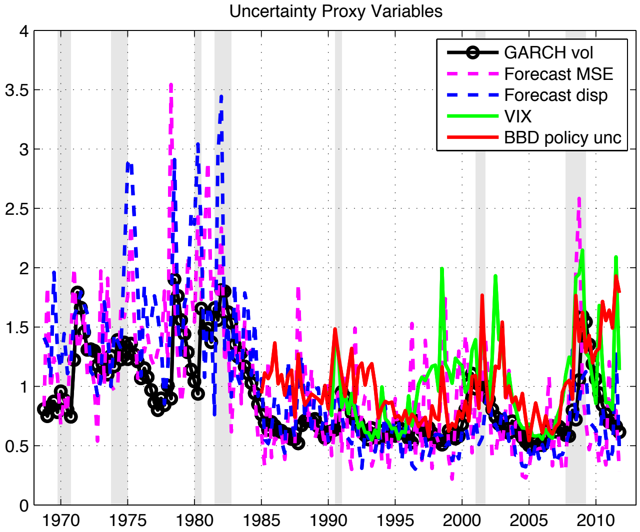
RGDP growth and forecasted growth



Parameter Estimates from Normal Shocks Model



How Does *Ut* Compare with Common Measures?



Corr U_t: GARCH 7%, MSE -3%, Disp 20%, VIX 36%, BBD 21%.

Are uncertainty shocks volatility shocks?

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

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

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

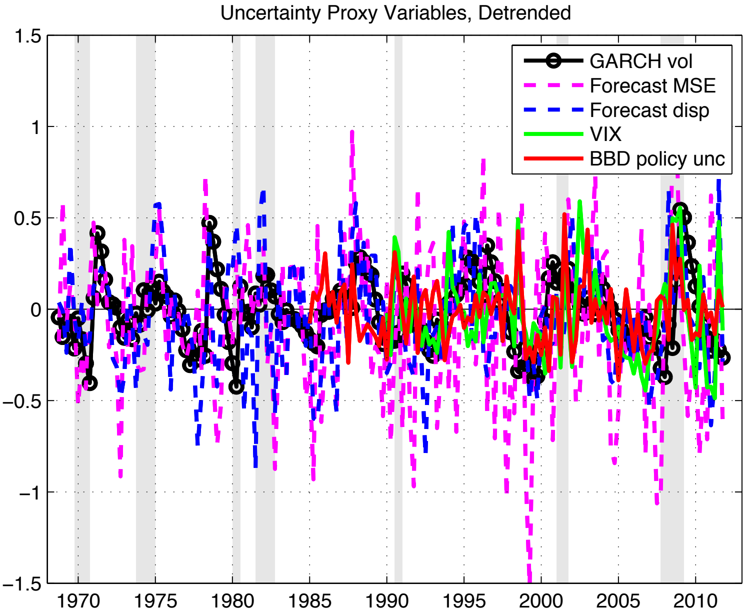
- If many forecasters, with indep errors, then $MSE_{t+1} = U_t$.

Proxy	Mean	Coeff Var	Autocorrel	Correl w/GDP
MSE	2.64	0.58	0.48	0.04
GARCH vol	3.65	0.37	0.9	0.06

- 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



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 $U_t = VOL_t$.

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

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

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

Considering Policy Uncertainty (2)

- If policy models and parameters are known, then we should see $MSE_{t+1} \approx VOL_t$.
- Do these two series look similar? No.

		mean	coeff var
Fed Gov't Spending	forecast MSE	6.36	0.53
	volatility	5.9	0.01
Interest Rate	forecast MSE	1	0.82
	volatility	0.47	0.65

- 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:

$$y_{t+1} = E\left(y_{t+1}|\mathcal{I}_{it}\right) + \eta_t + \epsilon_{it}$$

Then, uncertainty and forecast dispersion are

$$\begin{aligned} U_{it}^2 &= E\left[\left(\eta_t + \epsilon_{it}\right)^2 |\mathcal{I}_{it}\right] = Var\left(\eta_t|\mathcal{I}_{it}\right) + Var\left(\epsilon_{it}|\mathcal{I}_{it}\right) \\ D_t^2 &= \frac{1}{N}\sum_i \left(E\left(y_{t+1}|\mathcal{I}_{it}\right) - \overline{E}_t\right)^2 = \frac{1}{N}\sum_i Var\left(\epsilon_{it}|\mathcal{I}_{it}\right) \end{aligned}$$

Dispersion measures uncertainty with the following model assumptions:

1. $Var\left(\eta_t|\mathcal{I}_{it}\right) = 0$
2. $Var\left(\epsilon_{it}|\mathcal{I}_{it}\right) = Var\left(\epsilon_{jt}|\mathcal{I}_{jt}\right)$ for all i, j, t.