

Modeling Information, Learning and Expectations in Macroeconomics

Universitat Pompeu Fabra

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Private/heterogenous/dispersed information

Today:

- ▶ *Forecasting the Forecasts of Others* (Townsend JPE 1983)
- ▶ *Dynamic Higher Order Expectations* (Nimark WP 2010)

Private/heterogenous/dispersed information

- ▶ Every agent has his own “window to the world” but no agent is better informed than others on average
- ▶ A framework to think about disagreement and uncertainty about the plans and actions of other agents

Is it important?

- ▶ We need to solve quantitative models to answer that question
- ▶ The principal modeling difficulty: The infinite regress of “forecasting the forecasts of others” (Townsend 1983)

Solution strategies for models with private information

- ▶ Lagged revelation of shocks: Townsend (1983), Singleton (1987)
 - ▶ Not always realistic and can result in weird (kinked) IRF (Bacchetta and Van Wincoop (2006))
- ▶ Finite horizon: Allen, Morris and Shin (2006)
- ▶ Static choices: Woodford (2002), Morris and Shin (2002), Angeletos and La'o (2009)

Nimark (2010) shows how to solve models in which these assumptions are relaxed

The infinite regress of expectations: It's your choice!

Remember from last time: We could solve the Morris and Shin (2002) model with or without an explicit expression for higher order expectations:

- ▶ Either predict what you really care about

$$a_i = (1 - r) E[\theta | I(i)] + rE[\bar{a} | I(i)]$$

$$a_i = \kappa x_i + (1 - \kappa)y$$

- ▶ or write an equivalent expression with an explicit role for higher order expectations

$$a_i = (1 - r) \sum_{k=1}^{\infty} r^{k-1} \theta^{(k)}(i)$$

$$\theta^{(k)} = g^k(\theta - y) + y$$

We will discuss both approaches in a dynamic setting today

Some history

- ▶ Townsend's paper the first to recognize the infinite regress of expectations in a macro setting, though it was already well-known within game theory.
- ▶ Solution method:
 - ▶ Make assumption about revelation of state to make relevant history finite.
- ▶ The model itself is not so interesting.

But we will still talk about the model of Townsend. (It is part of our cultural heritage.)

- ▶ Also use Townsend's model to talk about hierarchical information structures (where the infinite regress problem can be avoided)

Forecasting the Forecasts of Others, Townsend JPE 1983

Output sector i

$$y_t^i = f_0 k_t^i$$

Market clearing price

$$\begin{aligned} P_t^i &= -b_1 Y_t^i + z_t^i \\ z_t &= \theta_t + \epsilon_t^i \end{aligned}$$

where

$$\theta_t = \rho \theta_{t-1} + v_t$$

and $\epsilon_t^i \sim N(0, \sigma_\epsilon^2)$ and $v_t \sim N(0, \sigma_v^2)$

Forecasting the Forecasts of Others, Townsend JPE 1983

The firms profit max problem:

$$\max_{\{k_t^i\}_{t=1}^{\infty}} E_0^i \sum_{t=0}^{\infty} \beta^t \left[P_t^i f_0 k_t^i - \frac{f_1}{2} (k_t^i)^2 - \frac{f_2}{2} (k_{t+1}^i - k_t^i)^2 \right]$$

$$f_0, f_2 > 0, \quad f_1 \geq 0$$

Decision rule

$$k_{t+1} = \lambda_1 k_t^i + \frac{f_0 \beta \lambda_1}{f_2} \sum_{j=0}^{\infty} (\beta \lambda_1)^j E(P_{t+1+j}^i | \Omega_t^i)$$

gives a law of motion for aggregate industry i capital stock

$$K_{t+1}^i = h_1 K_t^1 + h_2 M_t^i$$

where

$$M_t^i = E(\theta_t | \Omega_t^i)$$

Hierarchical information structure

- ▶ Industry 1 is "self contained":
 - ▶ Does not observe prices in any other industry
- ▶ Industry 2 observes prices in Industry 1, but there is no trade or other "real" interaction across sectors
 - ▶ Industry 2 uses observation of price in Industry 1 to form an estimate of θ_t

The only link between industries is that they both try to estimate the same unobservable state

Industry 1 filtering problem

By Kalman filtering

$$M_t^1 = \rho M_{t-1}^1 + G_t (z_t^1 - \rho M_{t-1}^1)$$

or with Townsend's notation:

$$M_t^1 = \alpha_0 M_{t-1}^1 + \alpha_1 z_t^1$$

Industry 1 law of motion

$$\begin{bmatrix} K_{t+1}^1 \\ M_{t+1}^1 \\ \theta_{t+1} \end{bmatrix} = \begin{bmatrix} h_1 & h_2 & 0 \\ 0 & \alpha_0 & \alpha_1 \rho \\ 0 & 0 & \rho \end{bmatrix} \begin{bmatrix} K_t^1 \\ M_t^1 \\ \theta_t \end{bmatrix} + \begin{bmatrix} 0 \\ \alpha_1 v_{t+1} + \alpha_1 \epsilon_{t+1}^1 \\ v_{t+1} \end{bmatrix}$$

Given the decision rule, industry 1 is solved.

Industry 2 filtering problem

Firms in Industry 2 also want to estimate the current value of θ_t and they observe as well as the history of prices in industry 1 so Industry 2's information set is

$$\Omega_t^2 = \{z_s^2, P_s^1, P_s^2, M_s^2, K_s^2 : s = 0, 1, 2, \dots, t\}$$

Industry 2 filtering problem

Standard form for the Kalman filter:

State equation

$$\begin{bmatrix} K_{t+1}^1 \\ M_{t+1}^1 \\ \theta_{t+1} \end{bmatrix} = \begin{bmatrix} h_1 & h_2 & 0 \\ 0 & \alpha_0 & \alpha_1 \rho \\ 0 & 0 & \rho \end{bmatrix} \begin{bmatrix} K_t^1 \\ M_t^1 \\ \theta_t \end{bmatrix} + \begin{bmatrix} 0 \\ \alpha_1 v_{t+1} + \alpha_1 \epsilon_{t+1}^1 \\ v_{t+1} \end{bmatrix}$$

Measurement equation

$$\begin{bmatrix} z_t^2 \\ P_t^1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 \\ -b_1 f_0 & 0 & 1 \end{bmatrix} \begin{bmatrix} K_t^1 \\ M_t^1 \\ \theta_t \end{bmatrix} + \begin{bmatrix} \epsilon_t^2 \\ \epsilon_t^1 \end{bmatrix}$$

Industry 2 filtering problem

We can then write the complete system as

$$\begin{bmatrix} K_{t+1}^1 \\ M_{t+1}^1 \\ \theta_{t+1} \\ K_{t+1}^2 \\ M_{t+1}^2 \\ E \left[K_{t+1}^1 \mid \Omega_{t+1}^2 \right] \\ E \left[M_{t+1}^1 \mid \Omega_{t+1}^2 \right] \end{bmatrix} = A \begin{bmatrix} K_t^1 \\ M_t^1 \\ \theta_t \\ K_t^2 \\ M_t^2 \\ E \left[K_t^1 \mid \Omega_t^2 \right] \\ E \left[M_t^1 \mid \Omega_t^2 \right] \end{bmatrix} + C \begin{bmatrix} v_t \\ \epsilon_t^1 \\ \epsilon_t^2 \end{bmatrix}$$

The mechanics of a hierarchical information structures

What breaks the infinite regress of expectations?

- ▶ Nested information sets and property of projections
 - ▶ Information set of Industry 1 nested in that of Industry 2 so that $\Omega_t^1 \subseteq \Omega_t^2$
 - ▶ We know from the properties of projections that $\mathcal{P}_1\mathcal{P}_2X = \mathcal{P}_1X$ and $\mathcal{P}_2\mathcal{P}_1\mathcal{P}_2X = \mathcal{P}_1X$ if $\Omega^1 \subseteq \Omega^2$

Intuition: You cannot predict the error of a strictly better informed agent so $\mathcal{P}_1(X - \mathcal{P}_2X) = 0 \implies \mathcal{P}_1X = \mathcal{P}_1\mathcal{P}_2X$

So what if firms in industry 1 also can observe prices in Industry 2?

Then we need to include industry 1's expectations about industry 2 expectations aboutindustry 1's expectations of θ_t ... and so on

- ▶ This is the infinite regress of expectations problem: Natural state representations tend to become infinite.

Townsend suggested that we assume

- ▶ that shocks are observed perfectly with a finite lag and
- ▶ use projection methods

This works since projections on a finite dimensional observations vector now spans the state and we can then compute

$$E[\theta_t | z_t^i, z_{t-1}^i, P_t^j, P_{t-1}^j, \theta_{t-2}]$$

Two reasons Townsend's model is special

Bugs or features?

- ▶ No real strategic interaction: Markets are only linked informationally
- ▶ In fact, there is no private information in equilibrium as shown by Sargent (JEDC 1991)

You'll be the judge.

Dynamic Higher Order Expectations Nimark (2010)

Solving dynamic models with private information

- ▶ Recursive formulation with an explicit role for higher order expectations

Impose common knowledge of rationality

- ▶ By it self does not solve the “infinite regress problem” but makes thinking about higher order expectations tractable
- ▶ Show that of expectations diminishes “fast enough” as order increases which allows for an arbitrarily good approximation
- ▶ Use Singleton’s (1987) model of asset pricing with disparately informed traders as vehicle for the argument

The Singleton (1987) asset pricing model

Trader j 's demand

$$z_t^d(j) = \frac{(E[p_{t+1} | I_t(j)] - (1 + \bar{r}) p_t)}{\gamma \delta}$$

Supply

$$z_t^s = \xi p_t + \theta_t + \epsilon_t$$

$$\theta_t = \rho \theta_{t-1} + v_t$$

The Singleton asset pricing model

Price Euler equation

$$p_t = \lambda \left(\int E[p_{t+1} | I_t(j)] dj \right) - \delta\gamma\lambda [\theta_t + \epsilon_t]$$

where

$$0 < \lambda < 1$$

Trader j 's information set

$$\begin{aligned} I_t(j) &= \{s_{t-T}(j), p_{t-T} : T \geq 0\} \\ s_t(j) &= \theta_t + \eta_t(j) \end{aligned}$$

Singleton:

$$I_t^S = \{s_{t-T}(j), p_{t-T} : T \geq 0; v_{t-T}, \epsilon_{t-T} : T \geq 2\}$$

Singleton's Solution method

Same as Townsend's:

- ▶ Assume that everything is revealed with a two period lag:

$$p_t = \lambda \left(\int E [p_{t+1} \mid s_t(j), s_{t-1}(j), p_t, p_{t-1}, \theta_{t-2}] dj \right) - \delta \gamma \lambda [\theta_t + \epsilon_t]$$

This allows for a finite and non-expanding dimension of state.

We will show how to solve the model without making this assumption.

Notation

Agents are indexed by $j \in (0, 1)$

$$\theta_{t|t}^{(0)} \equiv \theta_t$$

$$\theta_{t|t}^{(1)} \equiv \int E \left[\theta_{t|t}^{(0)} \mid I_t(j) \right] dj$$

$$\theta_{t|t}^{(2)} \equiv \int E \left[\theta_{t|t}^{(1)} \mid I_t(j) \right] dj$$

$$\theta_{t|t}^{(k)} \equiv \int E \left[\theta_{t|t}^{(k-1)} \mid I_t(j) \right] dj$$

Dynamic Notation

$$\begin{aligned}\theta_{t+1|t}^{(1)} &\equiv \int E[\theta_{t+1} | \Omega_t(j)] dj \\ \theta_{t+2|t+1|t}^{(2)} &\equiv \int E[\theta_{t+2|t+1}^{(1)} | \Omega_t(j)] dj \\ \theta_{t+k|\dots|t}^{(k)} &\equiv \int E[\theta_{t+k|\dots|t+1}^{(k-1)} | \Omega_t(j)] dj\end{aligned}$$

Notation cont.

Denote a vector consisting of a *hierarchy of expectations* (from order zero to k)

$$\theta_{t|t}^{(0:k)} = \begin{bmatrix} \theta_{t|t}^{(0)} \\ \theta_{t|t}^{(1)} \\ \vdots \\ \theta_{t|t}^{(k)} \end{bmatrix}$$

Constructing a law of motion for expectations using common knowledge of rationality

- ▶ Illustrate how common knowledge of rationality impose structure on higher order expectations
- ▶ A simple example (no economics yet)

Estimating an unobservable process

The true process is an AR(1)

$$\theta_t = \rho\theta_{t-1} + v_t$$

In period t agent j observes the private noisy signal $s_t(j)$

$$\begin{aligned} s_t(j) &= \theta_t + \eta_t(j), \\ \eta_t(j) &\sim N(0, \sigma_\eta^2) \quad \forall j \end{aligned}$$

Updating equation

$$\theta_{t|t}^{(1)}(j) = (1 - g_1) \rho \theta_{t-1|t-1}^{(1)}(j) + g_1 s_t(j)$$

Higher order estimates

A new state space system

$$\begin{bmatrix} \theta_t \\ \theta_{t|t}^{(1)} \end{bmatrix} = \begin{bmatrix} \rho & 0 \\ g_1 \rho & (1 - g_1) \rho \end{bmatrix} \begin{bmatrix} \theta_{t-1} \\ \theta_{t-1|t-1}^{(1)} \end{bmatrix} + \begin{bmatrix} 1 \\ g_1 \end{bmatrix} v_t$$

$$s_t(j) = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \theta_t \\ \theta_{t|t}^{(1)} \end{bmatrix} + \eta_t(j)$$

Higher order estimates

Agent j can now form expectations of actual and average first order expectations using the new updating equation

$$\begin{bmatrix} \theta_{t|t}^{(1)}(j) \\ \theta_{t|t}^{(2)}(j) \end{bmatrix} = \begin{bmatrix} \rho & 0 \\ g_1 \rho & (1 - g_1) \rho \end{bmatrix} \begin{bmatrix} \theta_{t-1|t-1}^{(1)}(j) \\ \theta_{t-1|t-1}^{(2)}(j) \end{bmatrix} \\ + \begin{bmatrix} g_1 \\ g_2 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix}' \left(\begin{bmatrix} \theta_t \\ \theta_{t|t}^{(1)} \end{bmatrix} - \begin{bmatrix} \theta_{t-1|t-1}^{(1)}(j) \\ \theta_{t-1|t-1}^{(2)}(j) \end{bmatrix} \right) + \eta_t(j) \right)$$

Higher order estimates

Again taking averages gives a law of motion for $\theta_{t|t}^{(0:2)}$

$$\begin{bmatrix} \theta_{t|t}^{(0)} \\ \theta_{t|t}^{(1)} \\ \theta_{t|t}^{(2)} \end{bmatrix} = \begin{bmatrix} \rho & 0 & 0 \\ g_1 \rho & (1 - g_1) \rho & 0 \\ g_2 \rho & (g_1 - g_2) \rho & (1 - g_1) \rho \end{bmatrix} \begin{bmatrix} \theta_{t-1|t-1}^{(0)} \\ \theta_{t-1|t-1}^{(1)} \\ \theta_{t-1|t-1}^{(2)} \end{bmatrix} + \begin{bmatrix} 1 \\ g_1 \\ g_2 \end{bmatrix} v_t$$

Bounded variance of higher order expectations

Lemma: The variance of trader j 's expectation of θ_t is bounded by the variance of θ_t , i.e.

$$E[\theta_t]^2 \geq E[\theta_t^{(1)}(j)]^2$$

Proof: Define trader j 's first order expectation error $\varepsilon_t^{(1)}(j)$ as

$$\theta_t \equiv \theta_t^{(1)}(j) + \varepsilon_t^{(1)}(j)$$

The error $\varepsilon_t^{(1)}(j)$ is orthogonal to $\theta_t^{(1)}(j) \in \Omega_t(j)$ so we have

$$E[\theta_t]^2 = E[\theta_t^{(1)}(j)]^2 + E[\varepsilon_t^{(1)}(j)]^2$$

The proof then follows from the fact that variances are non-negative so that

$$E[\theta_t]^2 \geq E[\theta_t^{(1)}(j)]^2$$

Bounded variance of higher order expectations

Lemma: The variance of the average expectation of θ_t is bounded by the variance of θ_t , i.e.

$$E[\theta_t]^2 \geq E[\theta_t^{(1)}]^2 \quad (1)$$

Proof: Trader j 's first order expectations have an MA representation with variance

$$E[\theta_t^{(1)}(j)]^2 = E[A(L)v_t]^2 + E[B(L)\epsilon_t]^2 + E[C(L)\eta_t(j)]^2 \quad (2)$$

Since $\int \eta_t(j) dj = 0 \forall t$ the average first order expectation is simply

$$\theta_t^{(1)} = A(L)v_t + B(L)\epsilon_t + \int C(L)\eta_t(j) dj \quad (3)$$

$$= A(L)v_t + B(L)\epsilon_t \quad (4)$$

with variance

$$E[\theta_t^{(1)}]^2 = E[A(L)v_t]^2 + E[B(L)\epsilon_t]^2 < E[\theta_t^{(1)}(j)]^2 \quad (5)$$

Bounded variance of higher order expectations

Proposition: The variance of higher order expectations of θ_t are bounded by the variance of lower order expectations, i.e.

$$E \left[\theta_t^{(k)} \right]^2 \geq E \left[\theta_t^{(k+1)} \right]^2$$

Proof: To prove the proposition, replace the definition of trader j 's first order expectations error $\varepsilon_t^{(1)}(j)$ in the proof of Lemma 1 with the definition of the k order expectation error

$$\theta_t^{(k-1)} - \theta_t^{(k)}(j) \equiv \varepsilon_t^{(k)}(j)$$

Noting that the k order error $\varepsilon_t^{(k)}(j)$ is orthogonal to $\theta_t^{(k)}(j) \in \Omega_t(j)$ allows for recursively establishing the proposition for $k = 2, 3, \dots$ by following the same steps as in the proofs of Lemma 1 and 2.

Bounded variance of higher order expectations

Proposition: The variance of higher order expectations of future expectations of θ_t are bounded by the variance of lower order expectations, i.e.

$$E \left[\theta_{t+k|\dots|t}^{(k-1)} \right]^2 \geq E \left[\theta_{t+k+1|\dots|t}^{(k)} \right]^2$$

Proof: To prove the proposition, replace the definition of trader j 's first order expectations error $\varepsilon_t^{(1)}(j)$ in the proof of Lemma 1 with the definition of the k order future expectation error

$$\theta_{t+k|\dots|t}^{(k-1)} - \theta_{t+k+1|\dots|t}^{(k)}(j) \equiv \varepsilon_{t+k+1|\dots|t}^{(k+1)}(j)$$

Again, since the k order error $\varepsilon_{t+k+1|\dots|t}^{(k+1)}(j)$ is orthogonal to $\theta_{t+k+1|\dots|t}^{(k)}(j) \in \Omega_t(j)$, the same recursive procedure as in Proposition 1 can be applied to establish the desired result for $k = 1, 2, 3, \dots$

Back to Singleton's asset pricing model

$$p_t = \lambda \left(\int E[p_{t+1} | I_t(j)] dj \right) - \delta \gamma \lambda [\theta_t + \epsilon_t]$$

where

$$0 < \lambda < 1$$

The Full Information Equilibrium Price

Iterate price Euler-equation forward

$$\begin{aligned} p_t &= -\delta\gamma\lambda(\theta_t + \epsilon_t) + \\ &\quad -(\delta\gamma\lambda)\lambda\rho\theta_t + \dots \\ &\quad \dots - (\delta\gamma\lambda)(\lambda\rho)^\infty \theta_{t+\infty} \end{aligned}$$

to get

$$p_t = -\frac{\delta\gamma\lambda}{1 - \lambda\rho}\theta_t - \delta\gamma\lambda\epsilon_t$$

The Private Information Equilibrium Price: Complications

Iterate price Euler-equation forward

$$p_t = \lambda \left(\int E [p_{t+1} | I_t(j)] dj \right) - \delta\gamma\lambda [\theta_t + \epsilon_t]$$

to get price as a function of higher order expectations of future θ

$$\begin{aligned} p_t = & -\delta\gamma\lambda (\theta_t + \epsilon_t) - (\delta\gamma\lambda)\lambda \int E [\theta_{t+1} | I_t(j)] dj \\ & + (\delta\gamma\lambda)\lambda^2 \int E \left[\int E [p_{t+2} | I_{t+1}(j)] dj | I_t(j) \right] dj \end{aligned}$$

or

$$p_t = -\delta\gamma\lambda\epsilon_t - \delta\gamma\lambda \sum_{k=0}^{\infty} \lambda^k \theta_{t+k|\dots|t}^{(k)}$$

An average expectations operator

Conjecture a law of motion for hierarchy

$$\theta_{t|t}^{(0:\infty)} = M\theta_{t-1|t-1}^{(0:\infty)} + N \begin{bmatrix} v_t \\ \epsilon_t \end{bmatrix}$$

Define new operator $H : \mathbb{R}^\infty \rightarrow \mathbb{R}^\infty$

$$H \equiv \begin{bmatrix} \mathbf{0}_{\infty \times 1} & I \end{bmatrix}$$

then higher order expectations of future fundamental are given by

$$\begin{aligned} \int E[\theta_{t+1} | I_t(j)] dj &= e_1' M H \theta_{t|t}^{(0:\infty)} \\ \int E \left[\int E[\theta_{t+2} | I_{t+1}(j)] dj | I_t(j) \right] dj &= e_1' (M H)^2 \theta_{t|t}^{(0:\infty)} \end{aligned}$$

...and so on.

The price function

The price of the asset can then be written as a function of the state

$$p_t = \begin{bmatrix} a_0 & a_1 & \cdots & a_\infty \end{bmatrix} \begin{bmatrix} \theta_{t|t}^{(0)} \\ \theta_{t|t}^{(1)} \\ \vdots \\ \theta_{t|t}^{(\infty)} \end{bmatrix} - \delta\gamma\lambda\epsilon_t$$

where the vector \mathbf{a} resembles a discounted geometric sum of expected future fundamentals

$$\mathbf{a} \equiv \begin{bmatrix} a_0 & a_1 & \cdots & a_\infty \end{bmatrix}$$

A finite dimensional approximation

Consider only the first \bar{k} orders of expectations

$$p_{\bar{k},t} = -\delta\gamma\lambda\epsilon_t - \delta\gamma\lambda \sum_{k=0}^{\bar{k}} \lambda^k \theta_{t+k|\dots|t}^{(k)}$$

We then have that

$$p_{\bar{k},t} = -\delta\gamma\lambda\epsilon_t - \delta\gamma\lambda \sum_{k=0}^{\infty} e_1' (\lambda MH)^k \theta_t^{(0:\bar{k})}$$

Define approximation error as

$$\Delta_{\bar{k}} \equiv p_t - p_{\bar{k},t}$$

A finite state representation

The variance of the price p_t is finite

Proof: We want to show that $E(p_t)^2 < \infty$. Taking variances of both sides of the expression for the equilibrium price we get

$$\begin{aligned} E(p_t)^2 &= (\delta\gamma\lambda)^2 \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} \lambda^{(i+j)} \text{cov} [\theta_{t+i|\dots|t}, \theta_{t+j|\dots|t}] \\ &\quad + 2\delta\gamma\lambda \sum_{j=0}^{\infty} \lambda^j \text{cov} [\theta_{t+i|\dots|t}, \epsilon_t] \\ &\quad + (\delta\gamma\lambda)^2 \sigma_\epsilon^2 \end{aligned}$$

We know from above that the covariances on right hand side are bounded and $0 < \lambda < 1$ we know that right hand side converges.

A finite state representation

Substitute in solution as function of current state state

$$p_t = \mathbf{a}\theta_{t|t}^{(0:\infty)} - \delta\gamma\lambda\epsilon_t$$

and take variances

$$\begin{aligned} E[p_t]^2 &= \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} a_i a_j \text{cov} \left[\theta_t^{(i)}, \theta_t^{(j)} \right] \\ &\quad + 2\delta\gamma\lambda \sum_{j=0}^{\infty} a_j \text{cov} \left[\theta_t^{(j)}, \epsilon_t \right] \\ &\quad + (\delta\gamma\lambda)^2 \sigma_\epsilon^2 \end{aligned}$$

Again, since we know that the price have finite variance, infinite sums on on right hand side must converge.

A finite state representation

The variance of the approximation error

$$\begin{aligned} E(\Delta_{\bar{k}})^2 &= \sum_{j=\bar{k}+1}^{\infty} \sum_{i=\bar{k}+1}^{\infty} a_i a_j \text{cov} \left[\theta_t^{(i)}, \theta_t^{(j)} \right] \\ &\quad + 2\delta\gamma\lambda \sum_{j=\bar{k}+1}^{\infty} a_j \text{cov} \left[\theta_t^{(j)}, \epsilon_t \right] \end{aligned}$$

must then tend to zero for the expression on previous slide to converge.

The law of motion of the expectations hierarchy

We want the form

$$\theta_{t|t}^{(0:\infty)} = M\theta_{t-1|t-1}^{(0:\infty)} + N \begin{bmatrix} v_t \\ \epsilon_t \end{bmatrix}$$

Process for actual state

$$\theta_t = \rho\theta_{t-1} + v_t$$

Trader j 's hierarchy updating equation

$$\theta_{t|t}^{(1:\infty)}(j) = M\theta_{t-1|t-1}^{(1:\infty)}(j) + K \left(S_t(j) - LM\theta_{t-1|t-1}^{(1:\infty)}(j) - Qc_t \right)$$

The law of motion of the expectations hierarchy

Signal vector is a function of the state

$$\int S_t(j) dj = L\theta_{t|t}^{(0:\infty)} + Qc_t$$
$$L = \begin{bmatrix} e'_1 \\ \mathbf{a} \end{bmatrix}, \quad Q = \begin{bmatrix} 0 \\ \frac{\lambda\psi}{1-\lambda\psi} \end{bmatrix}$$

We can write the average hierarchy updating equation as

$$\theta_{t|t}^{(1:\infty)} = (I - KL)M\theta_{t-1|t-1}^{(1:\infty)} + KLM\theta_{t-1|t-1}^{(0:\infty)} + KLN \begin{bmatrix} v_t \\ \epsilon_t \end{bmatrix} + K \begin{bmatrix} 0 \\ -\delta\gamma\lambda\epsilon_t \end{bmatrix}$$

The law of motion of the expectations hierarchy

Actual process and average hierarchy updating equation imply

$$M = \begin{bmatrix} \rho & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ KLM_- \end{bmatrix} + \begin{bmatrix} 0 & \mathbf{0} \\ \mathbf{0} & (I - KL) M_- \end{bmatrix}$$
$$N = \begin{bmatrix} e'_1 \\ KLN_- \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \mathbf{0} & -K_2\delta\gamma\lambda_- \end{bmatrix}$$

To solve the model, find a fixed point for M , N , a and δ

The solved model

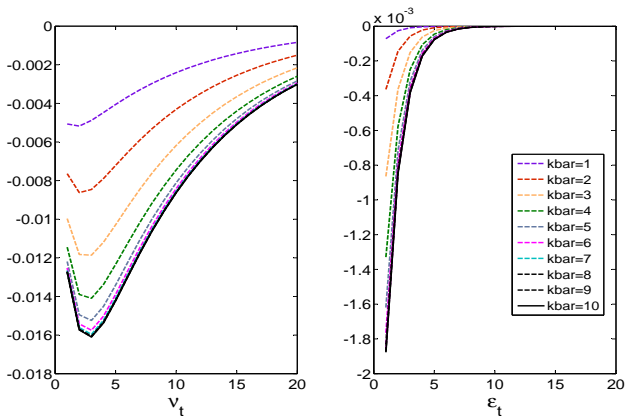
The solved model is in the form

$$\theta_{t|t}^{(0:\bar{k})} = M\theta_{t-1|t-1}^{(0:\bar{k})} + N \begin{bmatrix} v_t \\ \epsilon_t \end{bmatrix}$$

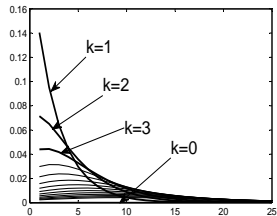
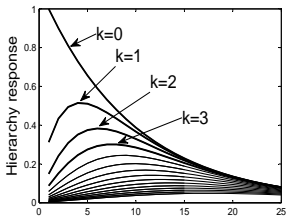
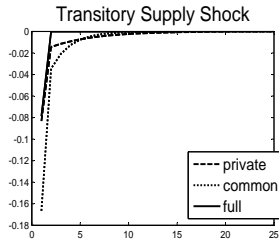
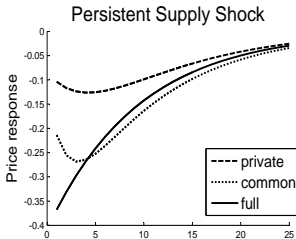
$$p_{\bar{k},t} = -\delta\gamma\lambda\epsilon_t - \delta\gamma\lambda e_1'(I - \lambda MH)^{-1}\theta_t^{(0:\bar{k})}$$

But we still need to choose \bar{k}

Choosing \bar{k} : Convergence in practice



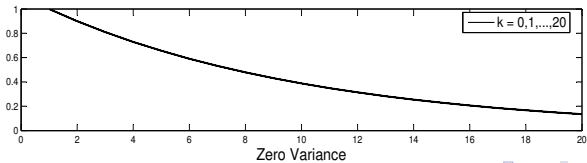
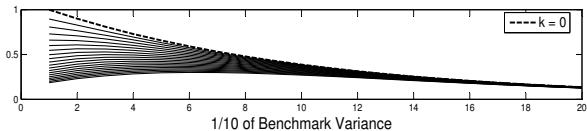
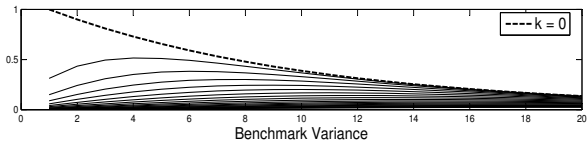
Price and hierarchy dynamics



The information revealed by prices

- ▶ Private information is not preserved in Townsend's (1983) model when equilibrium prices are observed: Sargent (1991), Kasa (2000) Pearlman and Sargent (2005)
- ▶ Walker (2007) makes similar claim about Singleton's model. But:
 - ▶ Does not prove this in Singleton's original set up
 - ▶ Makes additional assumption that the supply shock ϵ_t is directly observable
 - ▶ The price then reveals θ_t perfectly

IRF of hierarchy of θ_t and the variance of ϵ_t



The method in 3 steps

1. Impose structure on higher order expectations through common knowledge of rational expectations
2. Variance of expectations non-increasing with order of expectation
3. Impact of expectations decreasing with order of expectation

The method seems quite useful

- ▶ No need to assume lagged shock revelation
- ▶ Can handle dynamic choices in infinite horizon models
- ▶ Multi dimensional hidden state
 - ▶ E.g. Nimark (JME 2008) on pricing decisions in a general equilibrium macro model
- ▶ Endogenous hidden state
 - ▶ E.g. capital stock in RBC model with incomplete markets and idiosyncratic technology shocks (Graham and Wright 2007)
- ▶ Solution fast enough for empirical work (Melosi 2010, Nimark 2010)

That's it for today.