Herd-driven Business Cycles

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- Many recessions were preceded by booming periods of frenzied investment after introduction of new technology ("boom-bust cycle")
  - IT-led boom in late 1990s
  - to some extent, financial innovation-led housing boom in 2000s
- While standard practice in business cycle analysis is to treat them separately, another view is that booms and busts are two sides of the same coin
  - "booms sow the seeds of the subsequent busts" (Beaudry, Galizia and Portier, 2015)
  - extent and magnitude of expansion cause and determine depth of downturn
- Our objective is to develop a theory of (quasi-)endogenous boom-and-bust cycles

This Paper

- We embed herding features into a business cycle framework
  - imperfect information and social learning
  - build on Banerjee (1992), Bikhchandani et al. (1992)
  - instead of information cascades, we explore the ability of such models to generate slow-growing booms followed by sudden crashes
  - Under multidimensional uncertainty (Avery and Zemsky, 1998), agents may attribute observations to wrong causes, but with possibility of quick reversals in beliefs

The Story

- Boom-bust cycles as false-positives:
  - Technological innovations arrive exogenously with uncertain qualities
  - Agents have private information and observe aggregate investment rates
    - high investment likely indicates good technology
    - but since signals are endogenous variables, high investment may just reveal high *beliefs*
    - hence, if beliefs are sometimes biased, agents may be confused between a state with good technology and a state with bad technology but where agents hold optimistic beliefs
  - To allow for such beliefs shocks, we introduce common noise in private signals
    - more broadly any shock that resemble high state: signal dispersion, noise trader shock...

The Story

- Development of a boom-bust cycle:
  - Unusually large realizations of noise may send the economy on self-confirming boom where:
    - agents underestimate the extent of noise and mistakenly attribute high investment to technology being good
    - leads agents to take actions that seemingly confirm their assessment
    - at first investment rises, seemingly confirming beliefs...
  - However, agents are rational and information keeps arriving, so probability of being in false-positive rises
    - at some point, most pessimistic agents stop investing
    - suddenly, high beliefs are no longer confirmed by experience
    - sharp reversal in beliefs and collapse of investment $\Rightarrow$ bust
    - truth is generally learned in the end

Related Literature

- News/noise-driven cycle literature
  - Beaudry and Portier (2004, 2006, 2014), Jaimovich and Rebelo (2009), Lorenzoni (2009), Blanchard, Lorenzoni and L'Huillier (2013), etc.
  - Shares the view of boom-bust cycles as false-positives
  - Can view our contribution as endogenizing the information process for news cycles
- Herding literature
  - Banerjee (1992), Bikhchandani et al. (1992), Chamley (2004)
  - But early herding models have been criticized:
    - Rely crucially on agents moving sequentially and making binary decisions
    - Boom-busts only arrive for specific sequence of events and particular ordering of people
  - In our model, agents move simultaneously and learn from aggregates
    - Do not rely on a specific ordering of agents to generate cycle, but instead on the endogenous evolution of beliefs in the presence common noise
    - Closest to Avery and Zemsky (1998) for herding with multidimensional uncertainty

Related Literature

- Rational Bubbles
  - OLG: Samuelson (1958), Tirole (1985), Martin and Ventura (2012, 2015,...), Gali (2014), etc.
  - Risk shifting: Allen et al. (1993), Allen and Gale (2000), Allen et al. (2017)
  - Heterogeneous beliefs: Harrison and Kreps (1978), Allen et al. (1993)
  - Financial constraints: Kocherlakota (2009), Miao and Wang (2011), Barlevy (2014)
  - Our story is consistent with empirical definition of bubbles as "upward price movement over an extended range that then implodes" (Kindleberger, 1978) but inconsistent with theoretical definition as a wedge with fundamental value

Plan

1. Learning model
2. Business-cycle model with herding (under construction)

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Learning Model

- Simple, abstract model
- Time is discrete $t = 0, 1..., \infty$
- Unit continuum of risk neutral agents indexed by $j \in [0, 1]$

- Agents choose whether to invest or not, $i_{jt} = 1$ or 0
- Investment technology has common return

$$R_t = \theta + u_t$$

  - Permanent productivity component $\theta \in \{\theta_H, \theta_L\}$ with $\theta_H > \theta_L$
    - drawn once-and-for-all at $t = 0$ from prior

$$Pr(\theta = \theta_H) = p_0$$

  - Transitory component $u_t \sim$ iid F^u
- Investing incurs a cost c

- Agents receive private signal s_j drawn from distributions with pdf $f^s_{\theta+\xi}\left(s_j\right)$
  - denote CDFs by $F^s_{\theta+\xi}(s_j)$ and complementary CDFs by $\overline{F}^s_{\theta+\xi}(s_j)$
  - ξ is some common noise drawn from cdf F^{ξ}
    - captures the fact that agents learn from common sources (media, govt)
  - assume that F^s_x satisfies *monotone likelihood ratio property* (MLRP), i.e.,

$$\text{for } x_2 > x_1, s_2 > s_1, \quad \frac{f^s_{x_2}(s_2)}{f^s_{x_1}(s_2)} \geqslant \frac{f^s_{x_2}(s_1)}{f^s_{x_1}(s_1)} \quad \text{(MLRP)}$$

  - *Intuition:* a higher s signals a higher $\theta + \xi$

- Example:

$$s_j = \theta + \xi + v_j \text{ where } v_j \sim \mathcal{N}\left(0, \sigma^2_v\right)$$

Learning Model: Public Information

- In addition, all agents observe
  - return on investment R_t
  - measure of investors m_t (social learning)
- Measure of investors is given by

$$m_t = \int_0^1 i_{jt} dj + \varepsilon_t$$

where $\varepsilon_t \sim$ iid F^m captures informational noise or noise traders

Learning Model: Information Sets

- Beliefs are heterogeneous
- Denote public information to an outside observer at beginning of period t

$$\begin{aligned}\mathcal{I}_t &= \{R_{t-1}, m_{t-1}, \ldots, R_0, m_0\} \\ &= \{R_{t-1}, m_{t-1}\} \cup \mathcal{I}_{t-1}\end{aligned}$$

- The information set of agent j is

$$\mathcal{I}_{jt} = \mathcal{I}_t \cup \{s_j\}$$

Learning Model: Timing

Simple timing:

- At date 0: θ, ξ and the s_j's are drawn once and for all
- At date $t \geqslant 0$,
  1. Based on information $\mathcal{I}_{jt}$, agent j chooses whether to invest or not
  2. Production takes place
  3. Agents observe $\{R_t, m_t\}$ and update their beliefs

Learning Model: Characterizing Beliefs

- Multiple sources of uncertainty so must keep track of joint distribution for public beliefs:

$$\pi_t\left(\tilde{\theta},\tilde{\xi}\right) = Pr\left(\theta = \tilde{\theta}, \xi = \tilde{\xi} | \mathcal{I}_t\right)$$

- Heterogeneous beliefs so keep track of distribution of individual beliefs $\left\{\pi_{jt}\right\}_j$
- Fortunately, heterogeneity is one-dimensional and constant:
  - by the law of iterated expectations,

$$\begin{aligned}\pi_t\left(\tilde{\theta},\tilde{\xi}\right) &= Pr\left(\theta = \tilde{\theta}, \xi = \tilde{\xi} | \mathcal{I}_t\right) \\ &= E\left[\mathbf{1}_{\theta=\tilde{\theta},\xi=\tilde{\xi}} | \mathcal{I}_t\right] \\ &= E\Bigg[\underbrace{E\left(\mathbf{1}_{\theta=\tilde{\theta},\xi=\tilde{\xi}} | \mathcal{I}_{jt}\right)}_{\equiv \pi_{jt}(\tilde{\theta},\tilde{\xi})} | \mathcal{I}_t\Bigg]\end{aligned}$$

  - Distribution of beliefs is always centered on public beliefs with a known distribution!

Learning Model: Characterizing Beliefs

- For ease of exposition, simplify aggregate uncertainty to three states (slides only)

$$\omega = (\theta, \xi) \in \left\{ (\theta_L, 0), (\theta_H, 0), (\theta_L, \Delta) \right\} \text{ with } \theta_L < \theta_L + \Delta < \theta_H$$

  - $\omega = (\theta_L, \Delta)$ is the false-positive state: technology is low, but agents receive unusually positive news

- Just need to keep track of two state variables (p_t, q_t):

$$p_t \equiv \pi_t(\theta_H, 0) \text{ and } q_t \equiv \pi_t(\theta_L, \Delta)$$

Learning Model: Characterizing Beliefs

Let us characterize the distribution of private beliefs $\left(p_{jt}, q_{jt}\right)$:

- By Bayes' law,

$$p_{jt} = Pr\Big(\omega = (\theta_H, 0)\,|\mathcal{I}_t \cup \left\{s_j\right\}\Big) = \frac{Pr\left(\theta_H, 0, s_j|\mathcal{I}_t\right)}{Pr\left(s_j|\mathcal{I}_t\right)}$$

$$= \frac{p_t f^s_{\theta_H}\left(s_j\right)}{p_t f^s_{\theta_H}\left(s_j\right) + q_t f^s_{\theta_L+\Delta}\left(s_j\right) + \left(1 - p_t - q_t\right) f^s_{\theta_L}\left(s_j\right)}$$

$$\equiv p_j\left(p_t, q_t, s_j\right)$$

$$q_{jt} = Pr\Big(\omega = (\theta_L, \Delta)\,|\mathcal{I}_t \cup \left\{s_j\right\}\Big) = \frac{q_t f^s_{\theta_L+\Delta}\left(s_j\right)}{p_t f^s_{\theta_H}\left(s_j\right) + q_t f^s_{\theta_L+\Delta}\left(s_j\right) + \left(1 - p_t - q_t\right) f^s_{\theta_L}\left(s_j\right)}$$

$$\equiv q_j\left(p_t, q_t, s_j\right)$$

- Agent j solves the problem

$$\max_{i_{jt}\in\{0,1\}} E\left[i_{jt}\left(R_t - c\right)|\mathcal{I}_{jt}\right]$$

- Therefore,

$$i_{jt} = 1 \Leftrightarrow E\left[R_t|\mathcal{I}_{jt}\right] = p_{jt}\theta_H + \left(1 - p_{jt}\right)\theta_L \geqslant c$$

- In other words, agent j invests whenever $p_{jt} \geqslant \hat{p}$ where

$$\hat{p}\theta_H + (1 - \hat{p})\,\theta_L = c$$

- Under MLRP, individual beliefs are monotonic in s_j

$$\frac{\partial p_j}{\partial s_j}\left(p_t, q_t, s_j\right) \geqslant 0$$

- Hence, the optimal investment decision takes the form of a cutoff rule $\hat{s}\left(p_t, q_t\right)$ such that

$$i_{jt} = 1 \Leftrightarrow s_j \geqslant \hat{s}\left(p_t, q_t\right)$$

where $\hat{s}_t$ is such that

$$p_j\left(p_t, q_t, \hat{s}_t\right) = \hat{p}$$

- The measure of investing agents is

$$m_t = \overline{F}^{s}_{\theta+\xi}\left(\hat{s}\left(p_t, q_t\right)\right) + \varepsilon_t$$

- m_t is a noisy signal about $\theta + \xi$

Learning Model: Updating public beliefs

- After observing m_t, public beliefs are updated

$$p_{t+1} = \frac{p_t f^m \left(m_t - \overline{F}^s_{\theta_H} (\hat{s}_t) \right)}{\Omega}$$

and

$$q_{t+1} = \frac{q_t f^m \left(m_t - \overline{F}^s_{\theta_L + \Delta} (\hat{s}_t) \right)}{\Omega}$$

where $\Omega = p_t f^m \left(m_t - \overline{F}^s_{\theta_H} (\hat{s}_t) \right) + q_t f^m \left(m_t - \overline{F}^s_{\theta_L + \Delta} (\hat{s}_t) \right) + (1 - p_t - q_t) f^m \left(m_t - \overline{F}^s_{\theta_L} (\hat{s}_t) \right)$

- Similar updating rule with exogenous signal $R_t = \theta + u_t$

- Under MLRP, the distributions of private signals are FOSD-ordered

$$\overline{F}^s_{\theta_L}(\hat{s}_t) \leqslant \overline{F}^s_{\theta_{L+\Delta}}(\hat{s}_t) \leqslant \overline{F}^s_{\theta_H}(\hat{s}_t)$$

- Since $p_j(p_t, q_t, s_j)$ is monotonic in s_j, the distribution over beliefs $\{p_{jt}\}$ are also ordered FOSD:

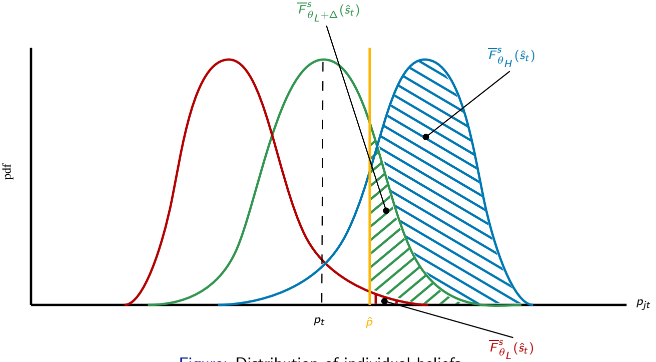
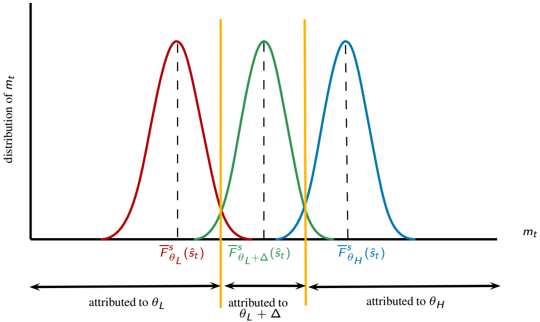


Figure: Distribution of individual beliefs

Information Feedback

Figure: Probability distribution of signal m_t

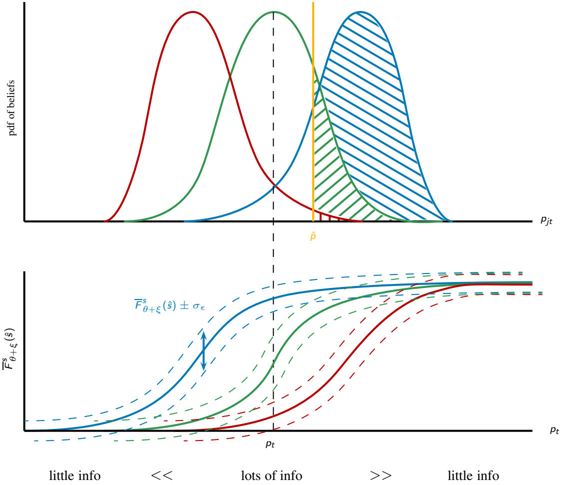


- Recall that

$$m_t = \overline{F}^s_{\theta+\xi}(\hat{s}_t) + \varepsilon_t$$

- High m_t is attributed to θ_H, low m_t to θ_L
  - But if $\theta_L + \Delta$ is close to θ_H, possibility of confusion with θ_H

- Amount of information from m_t is nonmonotonic:



- When p_t is extreme (high or low), m_t reveals almost nothing!
  - Allows for persistent "bubble" situations

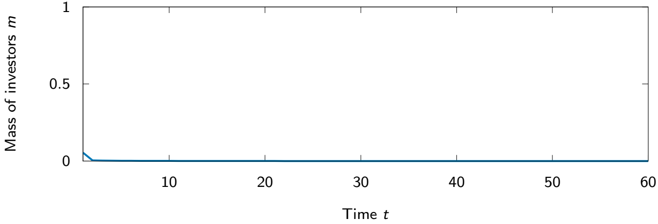
- Parametrization
  - Fundamentals: $\theta_h = 1.0$, $\theta_l = 0.5$, $\Delta = 0.4$, $c = 0.75$
  - Priors: $\mathrm{P}(\theta_h, 0) = 0.25$, $\mathrm{P}(\theta_l, \Delta) = 0.05$, $\mathrm{P}(\theta_l, 0) = 0.7$
  - Signals: Gaussian, e.g.:

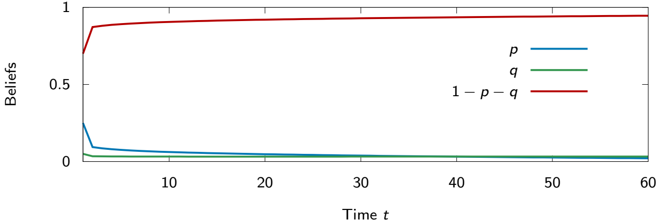
$$s_j = \theta + \xi + v_j \text{ with } v_j \sim \mathcal{N}\left(0, \sigma_v^2\right)$$

with $\sigma_v = 0.4$ (private), $\sigma_\varepsilon = 0.2$ (m_t), $\sigma_u = 2.5$ (R_t)

Simulations: True Negative

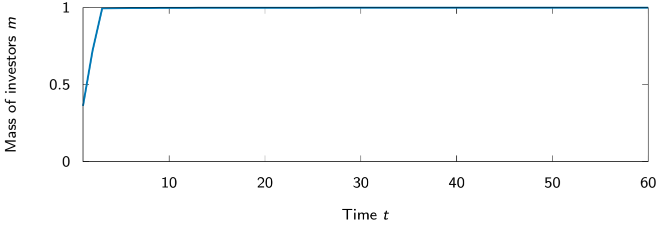
- True fundamental $(\theta_l, 0)$

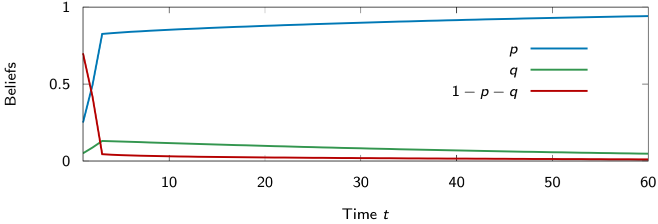




Simulations: True Positive

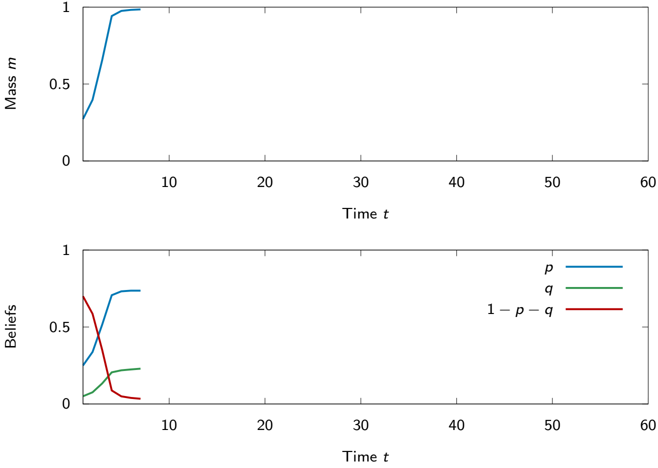
- True fundamental $(\theta_h, 0)$





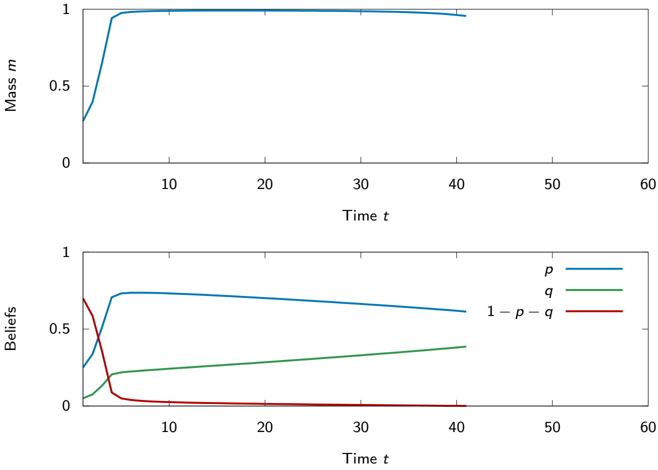
Simulations: False Positive

- True fundamental (θ_I, Δ)
- **Growth**

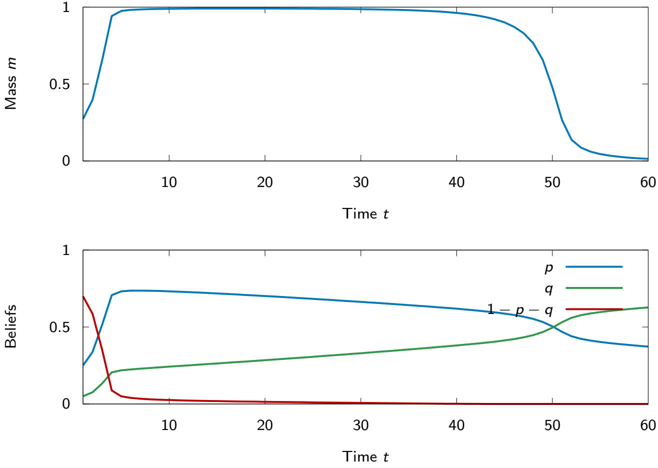


Simulations: False Positive

- True fundamental (θ_l, Δ)
- **Stagnation**

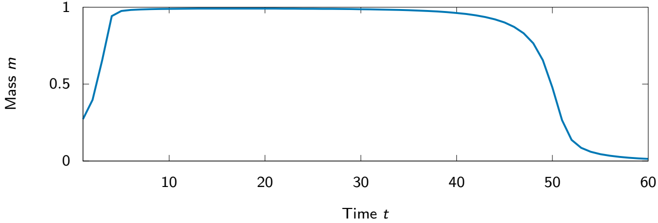


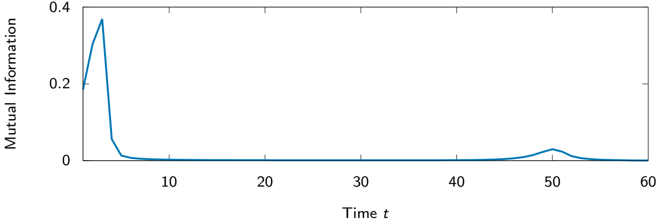
- True fundamental (θ_l, Δ)
- **Burst**



Simulations: False Positive

- True fundamental (θ_I, Δ)
- **Endogenous information contained in m**

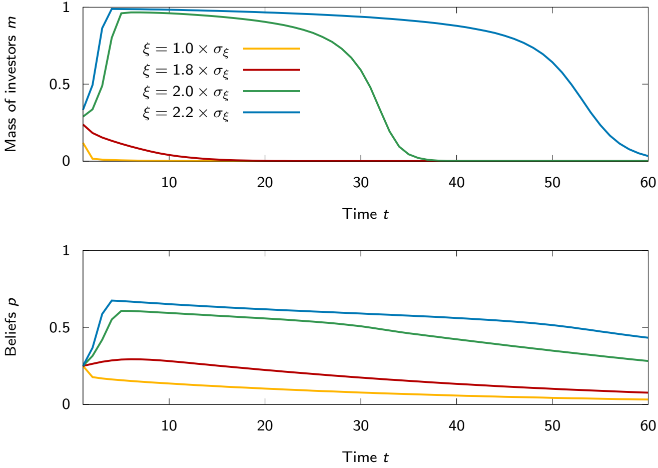




Simulations: Continuous ξ

- Previous simulations may look knife-edge
  - require state (θ_l, Δ) to be infrequent and resemble $(\theta_H, 0)$
- We now allow ξ to take a continuum of values
- Take-away:
  - small shocks ($<$1 SD) are quickly learned,
  - but unusually large shocks lead to boom-bust pattern

- True fundamental $\left(\theta_I = 0, \xi = \text{multiple of } \sigma_\xi\right)$



Additional Results

- Asymmetry: slow boom and sudden crash?
  - We extend to continuous arrival of private information ▸ Go
  - Initially, with little public information, distribution of private beliefs fans out, slowing the boom
  - Crash remains sudden because it arises later when public signals have accumulated and beliefs are less dispersed
- Welfare
  - Information externality: agents do not internalize how investment affects release of info
  - We study the social planning problem ▸ Go
  - Optimal policy leans against the wind to maximize collect of information
  - Implementation with investment tax/subsidy

Plan

1. Learning model
2. Business-cycle model with herding (under construction)

A News-driven Business Cycle Model?

- We want a model in which rising beliefs cause a boom, then a recession when beliefs collapse
  - Key difficulty is to generate comovement in absence of technology shock
    - Wealth effect reduces labor and output
    - For risk aversion greater than 1 (IES<1), want to move resources from rich to poor states: investment declines before realization of productivity
- Build on the news-driven business cycle literature
  - Beaudry and Portier (2004, 2014); Jaimovich and Rebelo (2009); Lorenzoni (2009)

Key Ingredients

1. New technology requires technology-specific capital
    - Investment is necessary to use the technology
    - No wealth effect without investment
2. Nominal rigidities
    - Without nominal rigidities, real interest rate spikes in response to beliefs and investment surge
        - can lower consumption and investment in traditional sector (recession or no boom)
    - Under nominal rigidities, if monetary policy is sufficiently accomodative, interest rate response is muted
        - consumption grows because of wealth effect from new technology
        - investment grows in order to benefit from new tech when it matures
        - hence, output rises with beliefs

- Three types of agents: households, entrepreneurs and retailers
- Three sectors: entrepreneur sector, retail sector and final good
  - Entrepreneur sector: technology choice, no nominal rigidities
  - Retail sector: buys the bundle of goods from entrepreneurs, subject to nominal rigidities
  - Final good: bundle of retail goods used for consumption and investment

- Unit measure of entrepreneurs indexed by $j \in [0,1]$
  - monopolistic producers of a single variety
- At any date, there is a traditional technology ("old") to produce varieties

$$Y_{jt}^{o} = A^{o} \left(K_{jt}^{o}\right)^{\alpha} \left(L_{jt}^{o}\right)^{1-\alpha}$$

- At $t = 0$, an innovative technology arrives ("new") unanticipatedly

$$Y_{jt}^{n} = A_{t}^{n} \left(K_{jt}^{n}\right)^{\alpha} \left(L_{jt}^{n}\right)^{1-\alpha}$$

- Importantly, each capital stock K_t^o and K_t^n are technology-specific
  - putty-clay, depreciates at rate δ
  - directly rented from households

Business Cycle Model: Entrepreneurs

- The new technology needs to mature to become fully productive

$$A_t^n = \begin{cases} A^o & \text{before maturation} \\ \theta & \text{after} \end{cases}$$

- The new technology matures with probability λ per period
- The true productivity θ is high or low $\theta \in \{\theta_H, \theta_L\}$ with $\theta_H > \theta_L$

- Each period, entrepreneurs choose which technology to use
  - for simplicity, assume no cost of switching so problem is static
  - denote m_t the measure of entrepreneurs that adopt the new technology
- A fraction μ of entrepreneurs is clueless when it comes to technology adoption
  - "noise entrepreneurs"
  - random fraction ε_t adopts the new technology

- Households live forever, work, consume and save in capital
- Preferences

$$E\left[\sum \beta^t \left(\frac{C_t^{1-\gamma}}{1-\gamma} - \frac{L_t^{1+\psi}}{1+\psi}\right)\right], \quad \sigma \geqslant 1, \psi \geqslant 0,$$

where $C_t = \left(\int_0^1 C_{jt}^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}}$ is the final good

- Quadratic adjustment cost in capital

$$\frac{\kappa}{2} I_{jt}^2, j = o, n$$

- Budget constraint

$$C_t + \sum_{j=o,n} \left(I_{jt} + \frac{\kappa}{2} I_{jt}^2\right) + \frac{B_t}{P_t} = W_t L_t + \sum_{j=o,n} R_{jt} K_{jt} + \frac{1+r_{t-1}}{1+\pi_t} \frac{B_{t-1}}{P_{t-1}} + \Pi_t$$

- Retail sector:
  - buys the bundle of goods produced by entrepreneurs
  - differentiates it one-for-one without additional cost
  - subject to Calvo-style nominal rigidity $\rightarrow$ standard NK Phillips curve
- Monetary authority follows the Taylor rule

$$r_t = \phi_\pi \pi_t + \phi_y y_t$$

- At $t = 0$, all entrepreneurs receive a private signal about θ from pdf $f^{s}_{\theta+\xi}$
  - same assumptions as before (MLRP, etc.)
- Social learning takes place through economic aggregates which reveal

$$m_t = (1-\mu)\,\overline{F}^{s}_{\theta+\xi}\,(\hat{s}_t) + \mu\varepsilon$$

- Assume public signal $S_t = \theta + u_t$ which capture media, statistical agencies, etc.
- No additional uncertainty, hence information evolves identically to learning model

Business Cycle Model: To Do

- Our goal is now to calibrate the economy using survey data (SPF or business analysts) to discipline information parameters
- Quantitatively evaluate the boom-bust cycles that arise (frequency, magnitude, asset prices, etc.)
- Evaluate how *leaning-against-the-wind* monetary policy can affect cycle and welfare

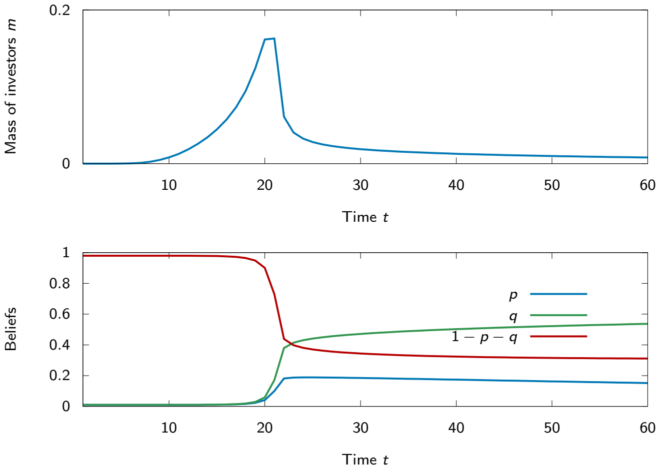
Technical challenges:

- Nonlinearities essentual to learning model but need linearization for DSGE model
- Use trick from Kozlowski et al. (2018) to keep track of joint distribution $\pi_t(\theta, \xi)$

Conclusion

- Introduce herding phenomena as a potential source of business cycles
- We have proposed a business cycle model with herding
  - people can collectively fool themselves for extended period of time
  - endogenous boom-bust cycles patterns after unusually large noise shocks
  - the model has predictions on the timing and frequency of such phenomena
- Provides rationale for leaning-against-the-wind policies which can substantially dampen fluctuations
- Quantification coming soon!

Continuous Arrival of Private Signals



Return

Welfare

- We adopt the welfare criterion from Angeletos and Pavan (2007)

$$V(p,q) = \max_{\hat{s}} E_{\theta,\xi}\left[\int_{\hat{s}} E\left[\theta - c|\mathcal{I}_j\right] dj + \gamma V\left(p',q'\right)|\mathcal{I}\right]$$

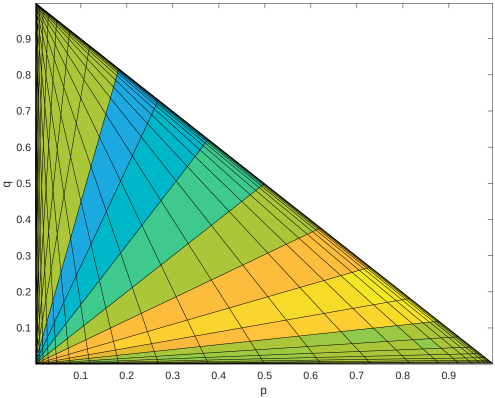
  where $\mathcal{I}$ is public info and $\mathcal{I}_j$ is individual info

- Crucially, the planner understands how $\hat{s}$ affects evolution of beliefs

Return

Welfare

- Entry threshold planner vs equilibrium

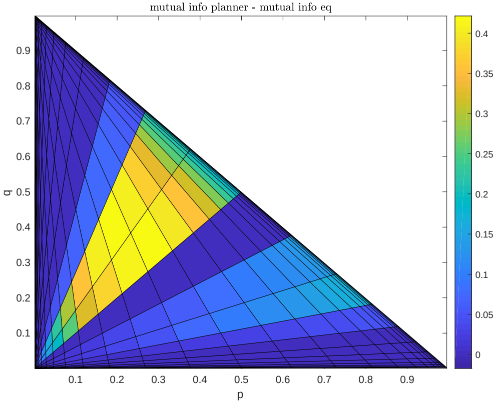


yellow = less investment in planner, green = same, blue = more

Return

Welfare

- More information is endogenously released in the efficient allocation



purple = same info in planner, light blue = more, yellow = a lot more

Return