Adaptive Business Cycles

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The Basic Idea

- Economic activity is characterized by booms and busts

Figure 1: Output and Investment Fluctuations - Source: King and Rebelo 2000
The Standard Approach

• Specifying a model of economic variables dependent on the *rational decisions* of agents

• Introducing random exogenous shocks to some parameters of the model

• Calibrating the steady state parameter of the model and those of the stochastic processes

• Studying the dynamics through simulations
Why Evolutionary Dynamics?

• In an evolutionary game agents do not necessarily choose the optimal strategy.
• Instead they can learn from past observations.
• In this learning process people often overshoot or undershoot their goals.
• This may be the cause of cycles as seen in economic data.
H. P. Minsky

- Financial Instability Hypothesis

- Our economy oscillates between robust and fragile states
- A financial crises requires the prior existence of a fragile financial structure (lots of illiquid assets)
According to Minsky…

- In a liquid asset dominated system there is a shift to speculative investments
- When speculative investment is rampant liquidity shortages present themselves leading to a recession
- The economy recovers from the recession with a robust, liquid asset dominated, structure
- This is the beginning of another cycle
Our Model

• We built a model based on Minsky’s views of economic cycles and liquidity management

• We focus on an example of short-term financing of illiquid assets: bank reserve management.

• This is based on Freixas and Rochet (1999) model of reserve management.
Reserve Management

- A bank wants to determine the quantity $R$ of liquid reserves to be held, out of a total of $D$ deposits.
- The remaining is invested in illiquid loans: $D - R = L$
- Reserves yield an interest rate $r$
- Loans yield $r_L$
- Loans yield a higher interest rate than reserves: $r_L > r$
Reserve Management

- Liquidity shock: each period depositors can withdraw a part of their deposits
- The amount of withdrawals $z$ is a random variable
- IF $z > R$, the bank has a liquidity shortage => It has to pay a penalty proportional to the shortage: $k(z - R)$
Reserve Management

Trade-off:

- reserves yield a smaller interest
- reserves hedge against liquidity shocks

- This trade-off is embedded in the payoff function of the bank.

\[ \pi = r_L (D - R) + rR - kE \left[ \max (0, z - R) \right] \]
Simplified Reserve Management

\[ \pi_{i \in \{h, l\}} = r_L (1 - R_i) - kE [\max (0, z - R_i)] \]

- We assume reserves do not yield any interest: \( r = 0 \)
- We adopt the following normalization:
  - \( D = 1, \ R = [0; 1] \) and \( L = 1 - R \)
- Only two discrete strategies are allowed
  - High reserves, \( R_h \)
  - Low reserves, \( R_l \)
3 Major Changes

• The interest rate depend on the population state

• Use belief learning instead of rational expectations $E[.]$

• Incorporate a logit decision rule
Determination of the Interest Rate

• For the bank the issue of a loan is a purchase of an illiquid asset

• The purchase of an illiquid asset yields $r_L$

• We assume
  • Asset supply: $S = P^\alpha, \alpha > 0$
  • Market clearing: $S = D$
  • Interest rate equation: $P = \frac{1}{1 + r_L}$

• This yields: $r_L = \frac{1}{D^{\frac{1}{\alpha}}} - 1$
Determination of the Interest Rate

• Aggregate asset demand is determined by the sum of loan issues (L) over the two strategies weighted by the respective frequencies in the population

\[ D = \sum_{i \in \{h,l\}} p_i L_i = \sum_{i \in \{h,l\}} p_i (1 - R_i) \]
Liquidity Shocks

- In each period, there can be either no shock or a total withdrawal of the deposits.

- As a baseline model we assume that $P(z = 1)$ is independent from the state (set to 0.5 in the baseline simulation).

- Alternative specification: assume that the probability of a withdrawal depends on the state of the population.
Belief Learning

• At the beginning of each period a bank can observe the current interest rate but does not know if there will be a liquidity shock or not

• We assume the bank estimates the probability of a shock using a form of backward-looking belief learning

\[
\tilde{E}_t(z_t) = \frac{1}{t-1} \sum_{k=0}^{t-1} \gamma^k z_{t-k} \sum_{k=0}^{t-1} \gamma^k
\]
Decision Rule

• We determine strategy shares using a logit decision rule.

\[ \pi_{it+1} = \frac{\Pi_{it}}{\sum_{j \in \{h,l\}} \Pi_{jt}} \]

\[ \Pi_{it} = e^{\beta \pi_{it}} \]

• \( \beta \) is the decisiveness
Simulation Parameters

- $R_h$ = reserve holding for the “High Reserve” strategy
- $R_l$ = reserve holding for the “Low Reserve” strategy
- $\alpha$ = supply elasticity of the illiquid asset
- $k$ = cost of liquidity shortage
- $P(z=1)$ = probability of a liquidity shock (withdrawal)
- $\beta$ = decisiveness
- $\gamma$ = memory of the learning process
Simulations
Rational expectation benchmark for the baseline calibration

- \( R_h = 0.9 \)
- \( R_l = 0.1 \)
- \( \alpha = 1 \)
- \( k = 4 \)
- \( P(z=1) = 0.5 \)
- \( \beta = 1 \)

- It can be useful to compare the evolutionary dynamics of the model with the rational expectation NE.
- If the probability distribution of the liquidity shock is known by the agents, the expected cost of a liquidity shortage is constant and does not vary with time.
- In other words the NE does not produce cycles. In our baseline model the NE share of each strategy is 0.5.
Simulations
Baseline calibration with perfect memory

- $R_h = 0.9$
- $R_l = 0.1$
- $\alpha = 1$
- $k = 4$
- $P(z=1) = 0.5$
- $\beta = 1$
- $\gamma = 1$
Simulations
Baseline calibration with short memory

- $R_h = 0.9$
- $R_l = 0.1$
- $\alpha = 1$
- $k = 4$
- $P(z=1) = 0.5$
- $\beta = 1$
- $\gamma = 0.5$
Belief Learning & Memory

• Only with short memory ($\gamma < 1$) our model displays fluctuations

• The assumption of short memory tries to incorporate the principle that “recent success breeds a disregard for the possibility of failure” (Minsky 1977, p. 146)
Simulations
Preferred calibration

- $R_h = 0.9$
- $R_l = 0.1$
- $\alpha = 0.7$
- $k = 4$
- $P(z=1) = 0.5$
- $\beta = 1$
- $\gamma = 0.7$
Simulations

Preferred calibration
Interest rate

\begin{itemize}
\item \( R_h = 0.9 \)
\item \( R_l = 0.1 \)
\item \( \alpha = 0.7 \)
\item \( k = 4 \)
\item \( P(z=1) = 0.5 \)
\item \( \beta = 1 \)
\item \( \gamma = 0.7 \)
\end{itemize}
Simulations

Effect of decisiveness

- $R_h = 0.9$
- $R_l = 0.1$
- $\alpha = 0.7$
- $k = 4$
- $P(z=1) = 0.5$
- $\gamma = 0.7$

- $\beta = 0.1$

- $\beta = 10$
Making the Probability of Shocks Endogenous

• As an alternative specification, we will assume that the probability of a withdrawal depends on the state of the population in terms of liquidity.

• Intuition: the more the illiquid the bank system is the more likely depositors are to withdraw funds out of fear of a credit crunch.

• \( P(z=1) \) is increasing in total loans \( D \)

\[
P(z_t = 1) = \frac{e^{\rho D_t}}{1 + e^{\rho D_t}}
\]
Simulations
Probability of a shock depends on population state

- \( R_h = 0.9 \)
- \( R_l = 0.1 \)
- \( \alpha = 0.7 \)
- \( k = 4 \)
- \( \rho = 1 \)
- \( \beta = 1 \)
- \( \gamma = 0.7 \)
Simulations

Interest rate
Probability of a shock depends on population state

- $R_h = 0.9$
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Simulations

Interest rate

Probability of a shock depends on population state

- \( R_h = 0.9 \)
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- \( \gamma = 0.7 \)
Conclusions

• With a sufficiently short memory, the model displays wide fluctuations, ranging from periods where 80% of banks are liquid to periods where only 40% are liquid.

• This result replicates the basic behavior of a system oscillating between robust and fragile financial structures