Agent-Based Computational Economics

Overview of the

Santa Fe Artificial Stock Market Model

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Basic References (See the Econ 308 Syllabus for Links)

https://www2.econ.iastate.edu/tesfatsi/syl308.htm

Ref.[1] ** L. Tesfatsion, **"Stock Market Basics"**

Ref.[2] ** L. Tesfatsion, **"Rational Expectations, the Efficient Market Hypothesis, and the Santa Fe Artificial Stock Market Model"**

Ref.[3] * L. Tesfatsion, **"Detailed Notes on the Santa Fe Artificial Stock Market Model"** (***NOTE:*** Ref.[3] contains a detailed glossary of terms. Also, the equation numbers appearing below in this slide-set are the same as in Ref.[3].)

Ref.[4] * R. Axtell, **"ACE Financial Market Modeling"**, VII Trento Summer School, July 2006

Ref.[5] * B. LeBaron, **"Building the Santa Fe Artificial Stock Market,"** Working Paper, Brandeis University, June 2002.
https://www2.econ.iastate.edu/tesfatsi/BuildingTheSFASM.BLeBaron.pdf

Introduction to the
Santa Fe Artificial Stock Market (SF-ASM) Model

- Originated in work at the Santa Fe Institute (SFI) in the late 1980s and early 1990s.
- **Five Developers of the SF-ASM:**
  - Blake LeBaron (economics);
  - W. Brian Arthur (economics);
  - John Holland (psychology/EE/CS, and father of GAs);
  - Richard Palmer (physics);
  - Paul Taylor (computer science).

The SM-ASM Model … Continued

- **Seminal Research:** One of the earliest attempts to develop and implement a ***computational financial market model with heterogeneously learning traders***.
- Relatively simple model that attempts to address several important and controversial questions in financial economics.
- Many modeling issues not satisfactorily resolved by the SF-ASM model have been taken up in later research; see, for example, ref. [4].

Basic Objectives of the Authors

- Provide a test-bed for exploring the **rational expectations hypothesis (REH, Ref.[2])**
- Consider a traditional stock market model with traders assumed to satisfy the REH
- Replace traditional REH traders with traders who learn to forecast stock prices over time
- Study dynamics around a well-studied REH equilibrium **(fundamental pricing, Ref.[1])**

Basic Author Objectives … Continued

- Examine whether the introduction of trader learning helps to explain empirical observations.
- In particular, does it help to explain well-documented **financial anomalies,** such as **deviations of stock prices from “fundamental values”** ?
- Compare statistical characteristics of price and trading volume outcomes (model outcomes vs. actual empirical outcomes).

Basic Model Features (cf. Ref.[3])

- Discrete-time model: t = 0,1,2,…
- Market participants consist of N stock market traders plus an "auctioneer"
- ***KEY ASSUMPTION:*** Traders are identical **except** that each trader **individually** forms expectations over time through inductive learning.
- Each trader has same initial wealth W_0 in the initial time period.

Basic Model Features… Continued

- Financial assets available for purchase at beginning of each period t = [t,t+1):

  - ★ **Risk-free asset F** (∞ supply) paying a constant known 1-period net return rate r

  - ★ **N shares of a risky stock A**. Each share

    - pays an ***uncertain*** dividend d_{t+1} at the end of each period t (beginning of each period t+1);
    - has an ***uncertain*** one-period net return rate R_t over each holding period t.

Basic Model Features … Continued

- Let p_t denote the **price of a share of the risky stock A at time t**

- The **expected net return rate R_t on this share over period t** (i.e. from time t to time t+1) is defined as

$$R_t = [p^e_{t+1} - p_t + d^e_{t+1}]/p_t$$

- This definition implies that

$$p_t = [d^e_{t+1} + p^e_{t+1}]/[1 + R_t]$$

Basic Model Features … Continued

- The expected net return rate R_t on a share of the risky stock A over period t satisfies:

$$p_t = [p^e_{t+1} + d^e_{t+1}]/[1 + R_t]$$

- **Basic rule of thumb for an investor in period t:**

  Given r = net return rate on the risk-free asset, ***SELL*** shares of A in period t if $R_t < r$ because this implies p_t is ***GREATER THAN*** the current fundamental value of these shares:

$$p^f_t = [p^e_{t+1} + d^e_{t+1}]/[1 + r]$$

Basic Model Features… Continued

- **Stock Dividend d_t** paid at beginning of each period t = [t,t+1) is generated by a random process unknown to the traders (see equ.(1) in Ref.[3])

- Wealth-seeking traders have identical **utility of wealth function U(W)** exhibiting constant absolute risk aversion.

Basic Model Features... Continued

- In beginning of each period t, each trader chooses a **portfolio (X,Y)**, where X = holdings of risky stock A and Y=holdings of risk-free asset F.
- Each trader's objective in period t is to maximize his **expected utility of wealth E U(W_{t+1})** subject to the constraint

(2) W_{t+1} = Value in period t+1 of the asset portfolio (X,Y) purchased in period t

Basic Model Features... Continued

- In beginning of each period t, each trader has a set of K if-then forecasting rules.
- Each forecasting rule forecasts the expected sum $[p_{t+1} + d_{t+1}]$ and generates an update of the rule's "forecast variance."

Forecast variance = a weighted average of a rule's past squared forecast errors (deviations between actual and forecasted price-plus-dividend sums).

Basic Model Features … Continued

- Form of an **if-then forecasting rule**:

Let VAR =: Updated forecast variance

$$E[p_{t+1} + d_{t+1}] = a[p_t + d_t] + b.$$

IF		THEN
Market state is in condition C′	→	Set values VAR′, a′, b′

Basic Model Features … Continued

- The **specificity** of a forecasting rule = number of specific conditions incorporated into its "if" condition statement C.
- A forecasting rule is **activated** if its "if" condition statement C matches the trader's current market state information.
- The **fitness** of a forecasting rule depends ***inversely*** on the rule's forecast variance (error rate) and ***inversely*** on its specificity (thus encouraging parsimonious info use).

Time Line of Activities in Period t

- Period-t dividend d_t^* is publicly posted.
- Each trader i=1,…,N determines a forecast

  $$E[p_{t+1} + d_{t+1}] = a'[p_t + d_t] + b'$$

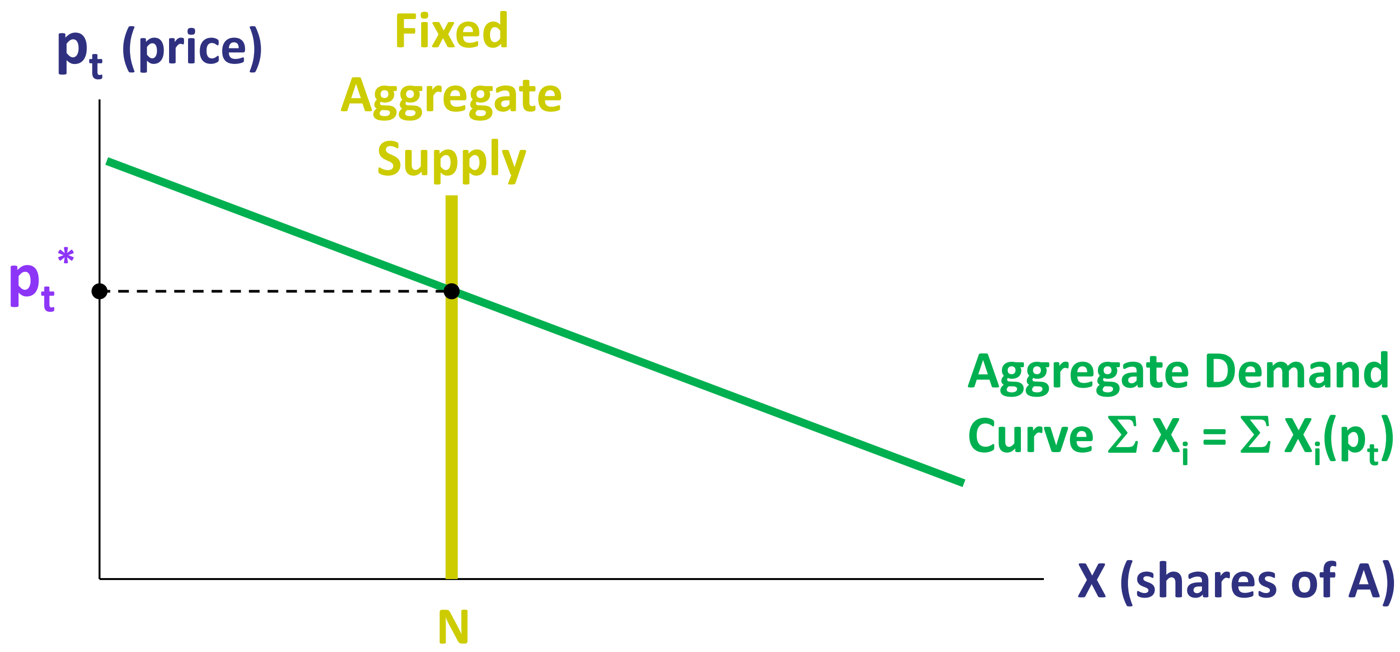
  as a function of the ***yet-to-be determined*** period-t market price $p_{t.}$

- He then generates a **demand function** giving his expected-utility-maximizing share holdings X_i as a function of p_t:

  (5) $$X_i = X_i(p_t)$$

Time Line in Period t … Continued

- Each trader i =1,…,N submits his demand function to the Auctioneer, who determines the ***period-t market clearing price*** p_t^* **:**



Time Line in Period t … Continued

- The Auctioneer publicly posts p_t^*.
- Each trader i purchases $X_i(p_t^*)$.
- Each trader i uses (p_t^*, d_t^*) to update the fitness of the forecasting rule he used in period t-1 to generate a forecast $E[p_t + d_t]$.
- Each trader i **with probability p_u** then updates his entire forecasting rule set via a genetic algorithm involving recombination, elitism, and mutation operations.

GA Classifier Learning

- Each trader i = 1,…,N updates his set of forecasting rules with an exogenously given probability p_u in each period t, making use of a **G**enetic **A**lgorithm (**GA**).
- Thus, **updating** of forecasting rule sets happens *in different time periods for different traders.*
- p_u is a very important model parameter since it determines the traders' "speed of learning".

GA Classifier Learning … Continued

- Current market state → 12-bit array

- Each bit position in this 12-bit array corresponds to a distinct possible feature of the current market state:

  -- Bit in kth position takes on **value 1** if kth feature is **true**

  -- Bit in kth position takes on **value 0** if kth feature is **false**

GA Classifier Learning…Continued

- **12-bit array** used to describe market state

- ***First six bit positions*** → ***Fundamental Features***

  Is the current market price above or below the fundamental price level in the previous time period?

  (six different possible discrepancy values)

GA Classifier Learning … Continued

- **Next four bit positions**

  → ***Technical Features***

  Is the current market price above an n-period moving average of past prices? **(four different values of n)**

- **Last two bit positions**

  → ***Fixed Bit Values*** **(no information)**

12-Bit Array for GA Classifier Learning

Bit	Condition
1	Price*interest/dividend > 1/4
2	Price*interest/dividend > 1/2
3	Price*interest/dividend > 3/4
4	Price*interest/dividend > 7/8
5	Price*interest/dividend > 1
6	Price*interest/dividend > 9/8
7	Price > 5-period MA
8	Price > 10-period MA
9	Price > 100-period MA
10	Price > 500-period MA
11	On: 1
12	Off: 0

Note on Rules 7-10:

MA =: Moving Average

= Weighted average of past observed prices

Note on Rules 1-6:

pr/d > 1 if and only if p > [p+d]/(1+r), i.e., if and only if the current price p for a share of the risky stock A exceeds the "fundamental" value of this share realized in the previous time period. **(** ***Refer back to slide 10.*** **)**

GA Classifier Learning … Continued

Why this market state description?

* Permits testing for the possible emergence of

  fundamental trading (heavy reliance on first six bit positions)

  <u>versus</u>

  technical trading (heavy reliance on next four bit positions)

  <u>versus</u>

  uninformed trading (heavy reliance on last two bit positions).

GA Classifier Learning … Continued

- Each forecast rule, taking form **if[C]-then[forecast this]**, is conditioned on a 12-bit market state C.

- Each bit in C has one of *three* possible values:

  1 (true), **0 (false),** or **# (I don't care).**

- **Specificity of C** =: Number of 1 and 0 bits in C

- C is said to **"match"** the actual 12-bit market state if:
  (a) C has a 1 or # symbol in every position for which the actual market state has a 1;
  (b) C has a 0 or # symbol in every position for which the actual market state has a 0.

Experimental Design

- **Key Treatment Factor: "Speed of Learning" Prob p_u**
  Controls when each trader updates their forecasting rule set in any given time period
- **Slow-Learning Regime: $p_u = 1/1000$**
  (GA learning invoked every 1000 trading periods on average for each trader)
- **Medium-Learning Regime: $p_u = 1/250$**
  (GA learning invoked every 250 trading periods on average for each trader)

Experimental Findings

- **Slow-Learning Regime: p_u = 1/1000**

  Simulated data resemble data generated for a ***rational expectations equilibrium (REE)*** benchmark, for which 100% market efficiency holds by assumption.

- **Medium-Learning Regime: p_u = 1/250**

  Complex outcomes -- market does not settle down to a recognizable equilibrium. Simulated data in accordance with many empirical "anomalies" (deviations from REH) seen in actual stock markets.

Frequency of Use of “Technical Trading”

Bits 7-10 in REE vs. Complex Regimes

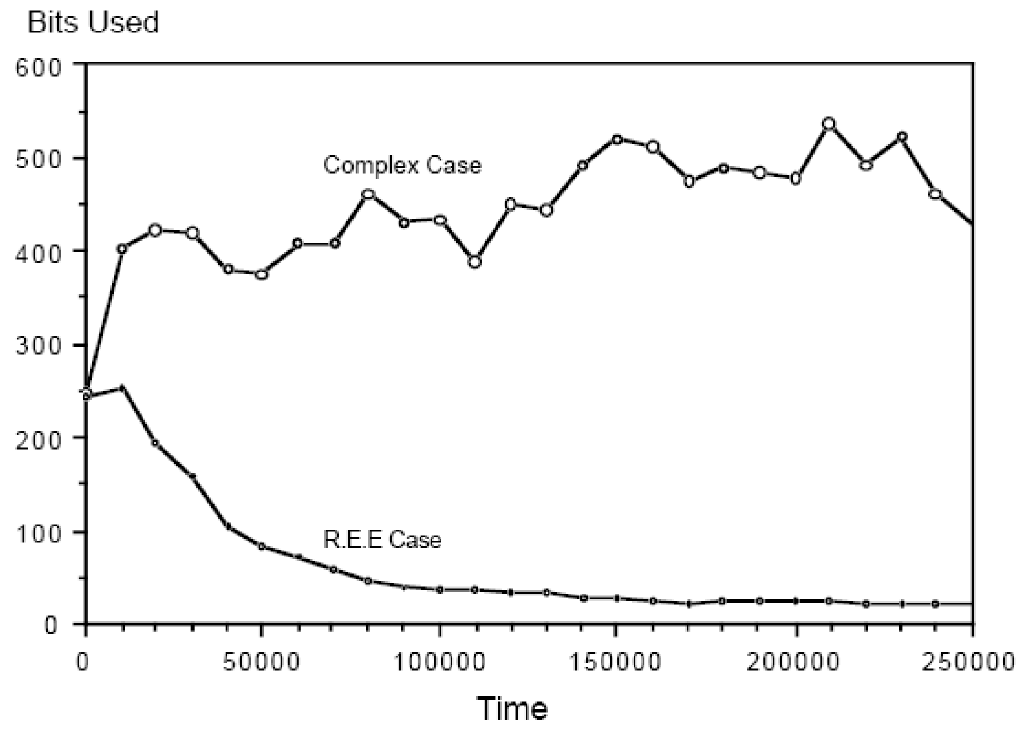


Figure 3. Number of technical-trading bits that become set as the market evolves, (median over 25 experiments in the two regimes).

Final Remarks

- For a balanced detailed critique of the Santa Fe Artificial Stock Market (SF-ASM), see the working paper by Blake LeBaron that appears below as **Ref. [5].**

- In this working paper, LeBaron discusses the advantages and disadvantages of various design aspects of the SF-ASM, including the use of “classifier systems” for the representation and evolution of forecasting rules.

Ref. [5] B. LeBaron, “Building the Santa Fe Artificial Stock Market,” Working Paper, Brandeis University, June 2002.
https://www2.econ.iastate.edu/tesfatsi/BuildingTheSFASM.BLeBaron.pdf