Building Financial Markets With Artificial Agents: Desired goals, and present techniques

Blake LeBaron
Graduate School of International Economics and Finance
Brandeis University
Waltham, MA
blebaron@brandeis.edu

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Abstract

Financial markets operate as a large interacting group of agents each in a constant struggle to better understand and interpret current prices and information. The complex interconnections between prices and information is probably more dramatic in financial markets than any other economic situation. Economic theory has been capable of describing many different financial equilibria, but it remains quiet on the types of dynamics that can occur while learning is still active and equilibrium is never quite obtained. Models of learning agents allow a direct attack on this problem. However, even though this approach may seem appealing at first it does come with many costs. The first of these is the modeling of the agents themselves. Boundedly rational agents can come in many forms, and an important question for theorizing is where to"set the dial" of rationality. This paper will describe some of the methods that have worked, and which directions look promising. Some methods for endogenously setting the level of rationality will be discussed. Finally, comparisons to the single agent, homogeneous belief world will be made, stressing why this is still a useful benchmark. A second issue involves the actual trading mechanisms, and this will be briefly discussed in relation to how outcomes can be affected. In closing, some of the policy questions centered on market stability and structure will be compared with certain computational issues.

1 Agents in simulated financial markets

This paper looks at several issues in the construction of artificial financial markets.[1] As a first step these markets will be defined, and distinguished from other agent based modeling techniques. Much of the work on agent based modeling looks at how simple agent/market mechanisms can solve large complex tasks with agents acting independently with no central control mechanism. In economic systems these self-organizing principles have been marveled at for quite some time.[2] However, the use of agents in economics and the other social sciences differs from some of the more practical applications in computer science and engineering. In social systems the emphasis is on building something that replicates reality as opposed to finding optimal solutions. A classic example of this is Schelling (1978) in which many social phenomena are shown to generate suboptimal behavior even with maximizing individuals. An important question for social scientists is to find where these deviations may occur in real world situations, and artificial markets are a part of this search.

Economics has relied on principles of equilibrium that assume the individual agents were able to solve well defined optimization problems which can be represented by global optimization problems in some specific cases. Getting into the actual behavior of individuals was far too costly, and opened up too many difficult questions. This has made many simple economic frameworks such as supply and demand curves, and representative agents the backbone of traditional economic theorizing. Agent based approaches in economics suggest another route which hopes to shed light on questions about where these simplifications were valid.

Financial markets are one of the most interesting of these cases because of the central role which prices play in conveying new information to the market. A simple example of this difference may help. When the price of a simple good goes up, most people view this only in connection with the immediate purchase and consumption of the good. They usually cut back their demand in response to this price change, and the economists' downward sloping demand curve works fine. In financial markets, this price change may encourage agents to buy more, since they might interpret a price increase as a good signal about a stock. They might also feel this was a speculative bubble that they might try to pursue. In all cases the dynamics can be much more complicated than the simple goods market.[3]

[1] For a survey of computationally oriented artificial financial markets see LeBaron (forthcoming 1999).

[2] See Hayek (1978) for the early references to economic self-organization.

[3] It should be noted that goods markets can get pretty complicated themselves. See Weisbuch, Kirman & Herreiner (1998) for agent models of the Marseille fish market, and Epstein & Axtell (1997) for more general spatial models of trade.

A second aspect of financial markets that makes them well suited for agent studies, is that the objectives of the agents are probably simpler than in other economic situations. For example, cars have many characteristics that are difficult to model correctly. This simplicity leads to easier construction of realistic agents.

This brief introduction gives some information on a few of the results from the Santa Fe Artificial Stock Market. A few of the markets details are given in section two. The results are presented in the third section, and the final section presents some challenges for the future.

2 Building an artificial financial market

This section briefly summarizes some of the design decisions and issues that went into the construction of the Santa Fe Artificial stock market.[4] It will concentrate on the agent construction, but other aspects of the market will also be covered.

The market consists of shares of stock and a risk free asset or bond. Traders decide on how much to hold of each given their forecasts of future movements in the stock market. The stock pays a dividend which has both predictable and unpredictable components.[5] The job of traders is to try to forecast future prices and dividends, and to combine these forecasts with their own preferences for risk and return.

The trading agents decide on their demand for shares according to the following demand function.

$$x_t^i = \frac{\hat{E}_t^i(p_{t+1} + d_{t+1}) - (1 + r_f)p_t}{\gamma \hat{\sigma}^2_{p+d,i}}, \tag{1}$$

This is a fairly routine myopic demand function in finance. It is connected to what is known as a constant absolute risk aversion utility function. The agents' demand for the shares is increasing in their forecast of future price and dividend, and decreasing in their estimate of the variance of the stock, $\sigma^2_{p+d,i}$. Many of the agent design issues come into building these forecasts from past time series data.

The set up of the market has already made two crucial decisions that may not be very appealing. First,

[4]The original paper using this market is Arthur, Holland, LeBaron, Palmer & Tayler (1997), and further results are in LeBaron, Arthur & Palmer (forthcoming 1999).

[5]It follows a linear autoregressive process of order one, where $d_{t+1} = \bar{d} + \rho(d_t - \bar{d}) + \epsilon_t$.

the agents are strictly myopic in that they only care about the next period. This obviously unrealistic assumption is made for tractability, and comparability with other results. Although this would be more interesting with preferences extending over several periods, this would bring in many more modeling issues that would greatly complicate things. Second, the agents are going to make a forecast, and then convert that into an action. Why not take the action directly? This is an interesting question from the standpoint of designing forecasting agents. It is not immediately obvious if the forecasting problem is well defined, as it is here, whether the agents should make a forecast and then get an action from the demand function, or whether the action should be implemented directly.

Forecasting is at the heart of this system. In financial modeling one is faced with trying to build boundedly rational agents who can convert a time series of past prices into a future forecast. The forecast representation should not limit the set of potential forecasts, but it should also allow easy interpretation of the way predictions are being made. A crucial aspect of forecasting is selecting which data should go into a forecast, and which information should be ignored. Much of the learning literature in economics ignores the fact that selecting what to ignore is a crucial aspect of economic decision making. The method used to do this here is based on classifier systems because it allows easy selection of relevant information, and rejection of useless information. However, many representations such as neural networks could also be used.[6]

The classifier system matches a predictor rule to a string of 1's and 0's which are a function of the current state of the market. This bit string consists of binary indicator variables giving such features as whether the price is above a moving average of past prices, and how the price compares to the current dividend. This simplification allows detailed analysis of whether the agents are using any of these pieces of information. A forecasting rule consists of a classifier string of 1's, 0's, and #'s, or don't care symbols. The ones and zeros must match the corresponding state of the market, and the don't care symbol matches either. These are connected with a forecasting rule given by (a_j, b_j, σ_j^2). This three vector is converted to a forecast using,

$$\hat{E}_t(p_{t+1} + d_{t+1}) = a_j(p_t + d_t) + b_j \tag{2}$$

[6]The use of the classifier is somewhat controversial in that they are known perform badly in dynamic situations. The best example of this is in Lettau & Uhlig (forthcoming 1999) in which it is shown that classifiers do not necessarily get the correct internal price structure to get to a dynamic solution. This is not an issue here since with myopic preferences this is one shot system, and the classifier is not asked to link actions together into a chain.

and σ_j^2 becomes the forecast variance, the denominator in equation 1. This forecast structure is extremely convenient since along with the market demand function in equation 1 it yields a linear demand for shares in the current price. This demand can then be aggregated and set equal to the total number of shares in the market to give a solution for the current price.

This system keeps the market in a temporary equilibrium at all times. There is no market imbalance, or traders who go away unsatiated at any time. Also, there is no need to build a complicated trading inventory or specialist system. These are interesting things to study in the future, but they add an extra level of complexity that clouds some of the basic issues.

As time goes by in the system the agents update their forecast rule books, which contain 100 different forecasting rules, using a genetic algorithm. The final primary design question comes into play in determining which fitness function should be used.[7] Rules are evaluated according to forecast accuracy, and penalized for the number of bits they have that are 0 or 1. This makes more complicated rules less attractive, and forces the agents to use the bits that they have set. The accuracy measure used is a rolling estimate of past squared forecast errors. It is not clear that this is the best measure to use, but it does have some useful properties. In some utility based decision making problems, it is the case that any risk averse agent will prefer the lower forecast error rule. A tricky aspect comes into play because the agents are forecasting both means and variances. This makes the decision of the agent to use lower variance forecasts a slightly more difficult problem. In general, it is not clear what action the agent should take given that the estimates of both the mean and the variance are going to be contaminated with noise.

3 Benchmarks and testing

One aspect of the economic setting used here is that it gives some useful benchmarks to compare with. In finance and economics an important benchmark is the case of rational expectations. This is essentially a fixed point at which everyone agrees on how the economy operates, and on how dividends are mapped into stock prices.

[7] This is probably more crucial than how mutation and crossover are implemented. These are described in detail in LeBaron et al. (forthcoming 1999).

For this market it is easy to show that an equilibrium where all traders are the same, and agree with each other exists, and is easy to characterize. It is simple to show that in the equilibrium the price will be a linear function of dividends. This also makes the optimal prediction of future prices and dividends very simple too since the dividend follows an autoregressive process of order 1. Agents in the rational expectations world would ignore all information except for current prices and dividends. This can easily be tested by finding out which information agents are looking at through the structures in their bit strings. Actually, in the equilibrium they should be ignoring all the available bitstring information.

Figure 1 shows the median fraction of bitstrings not set to don't care bits, #, for a set of 25 runs. These values were taken from the beginning of the market to period 250,000. The first run is labeled "fast learning" and refers to a GA run on average every 250 periods. The series labeled "slow learning" has a GA run on average every 1000 periods. In both cases it is clear that the fraction of bits set is dropping from its starting value which was set to 0.1 in the initialization. This drop off is due to the cost of additional bits in the forecasting rules.

If we turn to a specific part of the bit string a very different picture appears. Figure 2 looks at bits that depend only on the price as compared to several moving averages which vary in length from 5 to 500 periods. Remember that these are the bits that are concerned specifically with finding trends in the price series. The results of figure 2 show that in the fast learning case these bits are getting used in many of the agent forecasting rules, while in the slow learning case the bits are turned off. It appears that when agents learn at a relatively high speed they are more likely to find spurious patterns to trade on. Remember that these patterns only persist because others are using them. They are self reinforced through the trading mechanism.

The evidence from the agents' behavior is not the only piece of information available. We also have the time series results from the market. Table 1 presents results from several regressions of the following form.

$$p_{t+1} + d_{t+1} = a + b(p_t + d_t) + cI_t + \epsilon_{t+1}. \tag{3}$$

In the homogenous rational expectations equilibrium $p + d$ is a linear function of past $p + d$, and therefore other pieces of information should provide no forecasting value. The regression adds several information indicator variables which include two different price/moving average indicators. For the 5 day MA indicator, the values are insignificant in either learning case. For the 500 day indicator, the slow learning case shows no significant effect, but the fast learning case is significant, revealing statistically useful information from this indicator. The self-reinforcing behavior of agents has generated macro level features which are observable using standard time series analysis. Weak trends of this form are observable in actual price series.[8]

4 Bounded rationality and future design questions

The artificial stock market described here has made many arbitrary decisions on agent design. Many of these design questions remain open for future researchers. Agents in financial markets can be very difficult to build since they are often interested in difficult open ended time series forecasts for which there isn't an easy foundation from which to start. It is difficult to summarize an entire time series in a coherent way leaving its interpretation open to the agent. Several tools are possible for this, but none have proved to be more useful than others at the moment. The classifiers used in this market make it very easy to see which pieces of information are being ignored by agents. However, they may impose other unseen structures on the problem. One issue is that they may induce agents to look at certain pieces of information which might get ignored in a more open ended framework such as a neural network or genetic programming.

The actual complexity of the forecasting rules is another interesting issue. It is allowed to change here through additions and deletions to the rules, but one could argue that the rule system is relatively constrained. It would be nice to have rules evolved of varying levels of complexity as they are needed. Rational expectations models are interesting since the equilibrium requires very little computational power for the agents to maintain, while it may require very complex rules to get there. It is possible that this convergence path is a difficult one with many instabilities likely along the way. As rules get ever more complex they may approach a kind of brittleness or instability, making them useless in an environment with other very complex agents. Rationality is bounded because the path to the equilibrium is a difficult one, not because of agents' limited computing power. Relatively complex behavior simply becomes too brittle and

[8]See for example Brock, Lakonishok & LeBaron (1992).

specific.[9]

Technologically, this suggests forecasting techniques that can easily change their complexity, and might easily be evaluated in terms of this measure as well. Neural networks offer a possibility in this area. However, other methods might be useful to, such as more traditional time series forecasts and nonparametric techniques. However, adjusting this dial of time series intelligence is not an easy job. When it is not adjusted endogenously there will always be a nagging question about how much unexploited information might be left in the series, and would the results have looked different with more "sophisticated" agents.

One critical issue for all agent based markets is validation. Many of the systems with their many learning and evolving agents come at the cost of many free parameters. This leaves open the question of whether clever researchers can "fit" any phenomenon that has been observed in financial time series using an agent based approach. This criticism is a valid one, but it applies to most other economic models as well. The agent based model often does have more parameters connected to aspects of economic behavior, such as learning, for which our priors are very diffuse. A related problem is how to judge out of equilibrium behavior with boundedly rational agents. When used to test whether a rational expectations equilibrium is "learnable" their mission is quite simple. When they are being used to generate some kind of equilibrium dynamics far from the rational expectations equilibrium one needs to question the ways in which the agents were bounded much more severely. For example, in financial markets we would want to know that they don't leave too many opportunities for profitable trading open to others. Unfortunately, we are still not very well equipped to make these distinctions at the moment. One final aspect of validation is replicability. Unfortunately, computer simulations are not as easily transferred as analytic theories, and the desire for some kind of common platform is huge. There has been no convergence on any one platform, and at the moment it still seems too early to press for one. However, sometime in the future it will be nice to be able to exchange various agent and market structures as easily as analytic formulas can be moved around today.

One final aspect that is very relevant to policy makers in financial markets is the actual trading mechanism. What type of trading is being used? The market design described here is very simple with a straightforward auctioneer. The system could use more realistic trading system drawn from actual financial markets. This adds another level of complexity to the analysis, but another level of realism to the trading.

[9]See Axelrod (1984) and Lindgren (1992) for examples of this from repeated game theory.

This could allow intelligent agent systems such as this to detect certain differences among actual market mechanisms in terms of price convergence and transparency. Such questions are important both to policy makers and people involved in setting up different electronic trading systems.

5 Conclusions

Agent approaches to financial markets offer a radical new way to think about financial markets which by starting with individual trading players puts new emphasis on their interactions through the price system. The field is only in its infancy, and much remains to be done. However, financial theory is at a state where it is asking for new theories to help explains the large swings and capital flows seen in modern markets. Traditional theories have a difficult time with this behavior, and also offer few policy recommendations. In the future agent based methods may be used to help in the design of actual trading mechanisms leading to more stable global foundations for goods and financial flows.

References

Arthur, W. B., Holland, J., LeBaron, B., Palmer, R. & Tayler, P. (1997), Asset pricing under endogenous expectations in an artificial stock market, *in* W. B. Arthur, S. Durlauf & D. Lane, eds, 'The Economy as an Evolving Complex System II', Addison-Wesley, Reading, MA, pp. 15–44.

Axelrod, R. (1984), *The Evolution of Cooperation*, Basic Books, New York.

Brock, W. A., Lakonishok, J. & LeBaron, B. (1992), 'Simple technical trading rules and the stochastic properties of stock returns', *Journal of Finance* **47**, 1731–1764.

Epstein, J. M. & Axtell, R. (1997), *Growing Artificial Societies*, MIT Press, Cambridge, MA.

Hayek, F. A. (1978), Competition as a discovery process, *in* 'New Studies in Philosophy Politics, Economics and the History of Ideas', University of Chicago Press, Chicago, IL, pp. 179–190.

LeBaron, B. (forthcoming 1999), 'Agent based computational finance: Suggested readings and early research', *Journal of Economic Dynamics and Control* .

LeBaron, B., Arthur, W. B. & Palmer, R. (forthcoming 1999), 'Time series properties of an artificial stock market', *Journal of Economic Dynamics and Control* .

Lettau, M. & Uhlig, H. (forthcoming 1999), 'Rules of thumb versus dynamic programming', *American Economic Review* .

Lindgren, K. (1992), Evolutionary phenomena for social dynamics, *in* C. G. Langton, C. Taylor, J. D. Farmer & S. Rasmussen, eds, 'Artificial Life II', Addison-Wesley, Reading, MA, pp. 295–312.

Schelling, T. (1978), *Micromotives and Macrobehavior*, Norton, New York, NY.

Weisbuch, G., Kirman, A. & Herreiner, D. (1998), Market organization and trading relationships, Technical report, University of Marseille, Marseille, France.

Description	Fast Learning	Slow Learning
$MA(5)$	0.009	-0.008
	(0.013)	(0.007)
$MA(500)$	0.074	-0.025
	(0.014)	(0.015)

Table 1: Forecasting Regressions

Means over 25 runs. Numbers in parenthesis are standard errors estimated using the 25 runs.

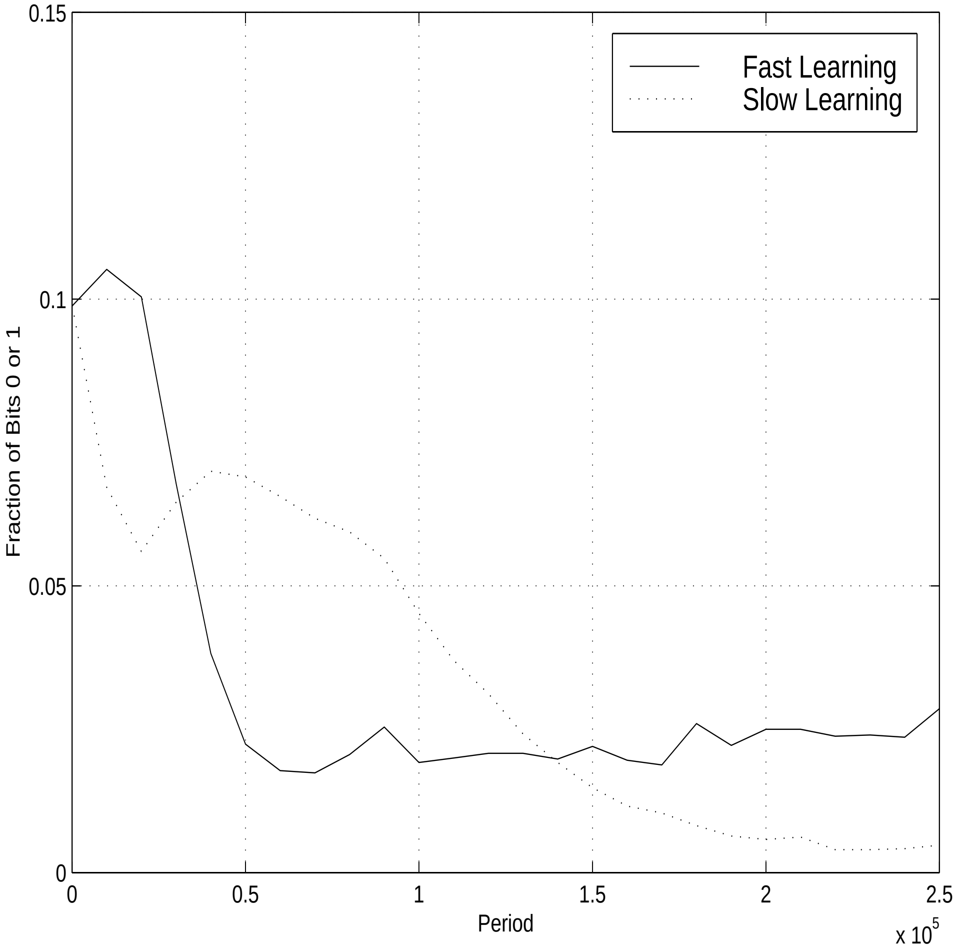

Figure 1: Average across all bits

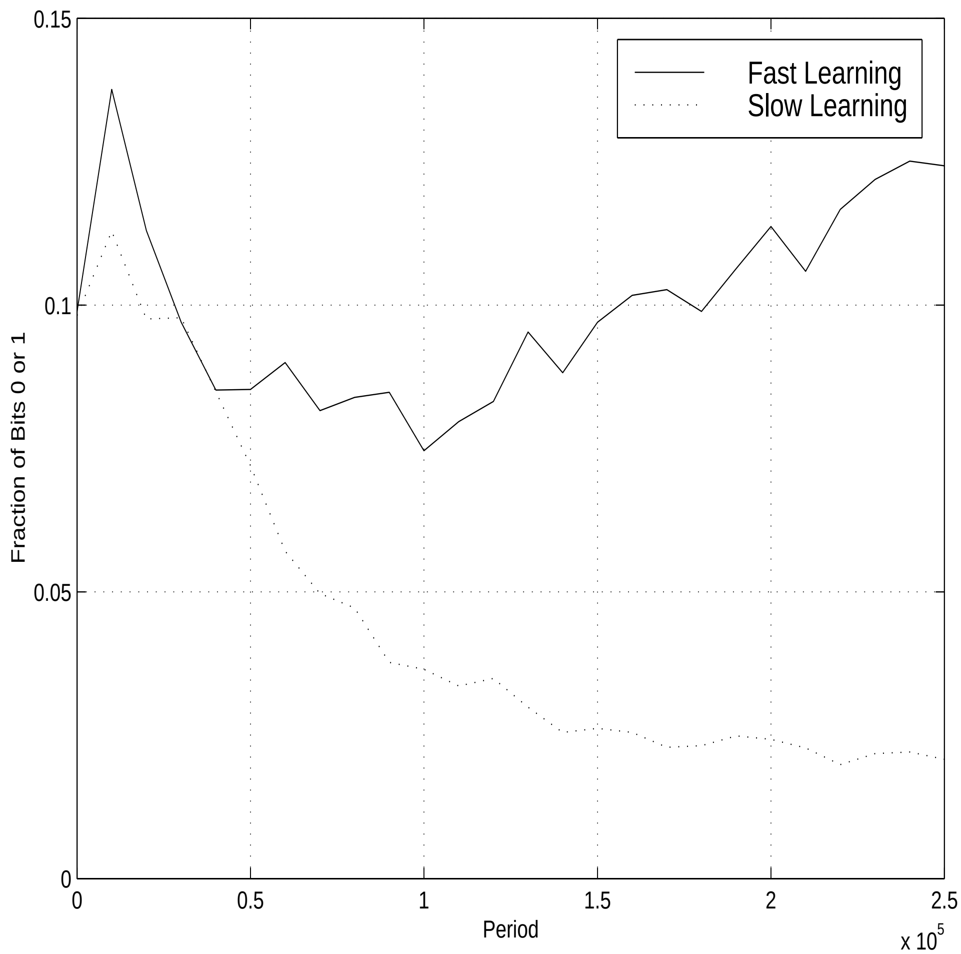

Figure 2: Technical trading bits only