THE FUTURE OF
AGENT-BASED MODELING
In the early 1960s, mathematician Benoit Mandelbrot began to study the prices of a number of commodities, of railroad securities, and of diverse interest rates. Although the nature of how the products were sold varied, he found the prices followed scaling laws; that is, when the price movements were observed at different time intervals, they showed similar patterns. Like fractals, which he named and made famous as modeling tools, these price series showed structure and self-similarity at different scales.

At the time, his findings were summarily dismissed, even disputed, as they contradicted popular economic theory that prices on financial markets followed the toss of a coin. “Hardly anybody knew what I was talking about,” he says now from his position as Sterling Professor of Mathematical Sciences at Yale University. “And if they found I was right, they didn’t publish it because it wasn’t fashionable.”

Mandelbrot continued to expand his work and by the 1980s other studies began to appear confirming his earlier findings. His 1963 paper on cotton pricing resurfaced as his best-known work on the topic and became the inspiration for modern-day agent-based modeling, particularly for the financial markets.

In October, Mandelbrot opened a day-long session in New York City on “Agent Models in Financial Economics,” hosted by SFI, Credit Suisse First Boston, and Legg Mason Capital Management. The seminar served as a time to reflect on the history of agent-based modeling, and SFI’s role in it, as well as give a blueprint for the future of the modeling approach. Leaders in the field who spoke at the event included Prediction Company co-founder and SFI researcher Doyne Farmer, Brandeis’s Blake LeBaron, MIT’s Andrew Lo, and Yale’s Shyam Sunder.

As computers become more and more sophisticated and markets continue to spew out an increasing amount of data on a daily basis, researchers are eagerly collecting data sets, and people in the financial industry are taking notice. Many suspect that if economists can build computer models illuminating patterns in various financial markets—particularly mapping volatility—in investors could minimize risk and reap the rewards. But the task is daunting and still in its infancy.

The models may not be able to prove or disprove an economic theory, but the practice can distill a certain aspect of a theory or illuminate a single mechanism. Most importantly, the models allow economists to study volatility, something long overlooked and long dismissed in terms of recognizing patterns. As Mandelbrot has written, “If the weather is moderate 95 percent of the time, can the mariner afford to ignore the possibility of a typhoon?”

While financial gain is a clear motivator for modeling financial markets, researchers outside of the commercial world are interested in the data and patterns they reveal for reasons other

by Janet Stites

OF FINANCIAL MARKETS
than potential wealth. For one, economists such as LeBaron, who has been involved in modeling since the early 1990s when he spearheaded the economics program at SFI, believes key debates in finance, such as those on market efficiency and rationality and the role behavior plays in decision making, might be deflated by analyzing the data of the markets. From the pure scientific perspective, particularly in regard to evolutionary biology, financial markets provide a good approximation to a crude fitness measure through wealth or return performance.

Doyne Farmer says researchers often use modeling as a way to try to understand statistical properties about the market that don’t involve things you can profit from, such as how big a price change can be, but not whether it goes up or down.

Early models, developed in the late 1980s and early 1990s included SFI’s own Santa Fe Artificial Stock Market (SF-ASM), the idea for which was fostered by economist Brian Arthur and genetic algorithm developer John Holland, who reached out to physicist Richard Palmer and computer scientist Paul Tayler (LeBaron joined the team in 1993). SF-ASM was one of the first studies to challenge the idea that financial markets are in equilibrium. Ultimately the model was merged with artificial intelligence guru Christopher Langton’s SWARM project. While the SF-ASM project is currently dormant, the SWARM version of the model is still available and people continue to experiment with it. Other models of that time came from French economist Alan Kirman, German economist Thomas Lux, and the team of Haim Levy, Moshe Levy, and Sorin Solomon.

Twenty years after the first models, there is not one prevailing method of modeling. “The field is very much all over the place,” says LeBaron. He notes that researchers tend to focus on one aspect of the market to model, whether it be prices, trading volume, or order flow.

LeBaron’s own work has shown how agent-based computational markets can generate patterns in liquidity and how these patterns are connected to generating realistic dynamics in both price and trading volume time series. Over the years, he has seen some unexpected results. “What I’ve seen is a tendency for the agents to occasionally concentrate on a small number of strategies,” he says. “When this happens it is hard to find other people to trade with and the market becomes unstable. Somebody needs to take the opposite side of the trade.” As a result, prices and trading volume may drop dramatically. It is during these times, LeBaron posits, that you see high volatility, big changes in pricing, and crashes.

The “agent” part of agent-based modeling can have many characteristics. In some models agents are programmed as a series of “if–then” statements: If A happens…Do B; If C happens…Do A. Others use genetic algorithms (GAs), allowing them to learn from their errors and evolve. Others use neural networks.

According to Farmer, the big challenge for agent-based modeling is this: Can it work well within the classical scientific method? “It’s hard to match up the model to the real world,” he says. “When you build the model, you’re forced to make a lot of ad-hoc assumptions about how the agents behave. Sometimes these assumptions are far from reality.”

Farmer uses the example of building a simulation of traffic in a particular city. “It’s easy to model the streets and
the stop signs or take into account the speed of a car on the freeway versus the speed of a car on a side street," he says. "It’s harder to determine how people make decisions, such as why they take a side street on a particular day instead of the freeway."

For his latest project, which models price formation, Farmer chose to work with data from the London Stock Exchange because it contains a complete record of actions by the traders as well as their effect on prices. He and his team began by assuming that the traders had “zero intelligence” (ZI), an approach initially developed by Yale’s Shyam Sunder and New York University’s Dan Gode in 1989.

"To get a feeling for how the trading process interacts with people’s decisions, we began by assuming that people are stupid and behave randomly," says Farmer. "The agents in the model randomly place orders, flipping coins to decide whether to buy or sell and what price to pay." As extreme as these assumptions are, they produced results that agree with the real data in many respects. "This shows that there are many aspects of market behavior whose explanation does not depend on rationality or even intelligent decision making—they just depend on the market structure," he says.

To improve on these results, Farmer uses an approach that he calls “empirical behavioral modeling,” which lies between the standard econometric and microeconomic approaches to model building. "Instead of imposing a preconceived model of human behavior, such as rationality," he says, “we look carefully at the data to find behavioral patterns." Farmer and his team then simulate the market based on the patterns, and make predictions about how prices will behave. “Note that we aren’t trying to predict the market,” he says. “We’re just trying to predict system

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Trading at the London Stock Exchange: Data allows SFI Research Professor Doyne Farmer and his team to work with a complete record of actions by the traders.
properties, such as why prices fluctuate more in one market than they do in another.” The resulting models make very good predictions about price volatility and the difference between buying and selling prices.

Yale economist Shyam Sunder uses the zero intelligence model to try to understand if there is intelligence in not being intelligent. “A degree of randomness may give one a strategic advantage,” Sunder says. “If I knew in a game of tennis that every time my opponent lobbed the ball to the baseline, my best shot is forehand down the line, and I continued to follow that rule, he could figure it out and react accordingly. If I introduced a degree of randomness, I might do better.”

Sunder’s initial foray into using agent-based modeling to better understand the financial markets came in 1989 when he had his MBA students teamed with computer science students to try to determine if, in fact, program trading (that is, trades made automatically by pre-programmed computers) had caused the stock market crash of 1987. He was especially interested in the problem because the idea that it had done so threatened to stifle the promise of technology in the financial markets.

The students found several surprising outcomes, including that short and simple trading strategies did well in the market, not because they were smart in the sense of being sophisticated, but because they were “there” all the time and were fast. What’s more, markets populated entirely by zero-intelligence traders, who had no ability to anticipate or strategize, were at least as efficient in aggregate, doing as well, or better than, the strategies devised by students which had been based on their own ideas.

Nearly two decades after the “program trading” scare of 1987, the use of technology on Wall Street has not lessened. Sunder warns, however, that before we can build a proper model, we need more data and we need to learn how to map expectations. He plans to continue to pursue the idea that randomness confers advantage by continuing to work with zero intelligence models. One advantage of his “keep the agents simple” strategy is that he doesn’t need additional computing power or data sets. “I can pretty much do what I need on my desktop computer,” he says.

While there is no comprehensive list of economists and scientists doing agent-based modeling of the financial markets, there are those whose work

Enhanced Mandlebrot sets depict complex geometric shapes. Buried deep within these mathematical forms are self-similar “fractal” patterns that emulate shapes found at higher levels. Natural systems often display similar behavior; for example, a coastline has a similar shape whether we view it from outer space or zoom in on just a few feet of beach front.
has, and continues to, contribute to the foundation of the field. Teams like Haim Levy, Moshe Levy, and Sorin Solomon have gotten much attention for using “microscopic simulation” to model markets, a methodology that was developed to solve physics problems. The model uses a computer to represent and keep track of individual elements in order to investigate otherwise intractable complex systems.

Another researcher who has been a pioneer in modeling financial markets is economist Alan Kirman, currently at Princeton’s Institute for Advanced Study, on leave from the University of Marseilles. He develops models with the underlying idea that agents in the markets meet each other and learn to trade together. They imitate each other and are influenced by what others expect. “The fundamental difficulty in modeling financial markets is that you cannot treat the traders as one glorified average individual,” he says. “You have to handle the fact that the behavior of the aggregate is basically different from that of the individuals that make it up.”

The modeling work of former SFI graduate student Vince Darley, of London-based consulting firm Eurobios UK, gained attention when he was asked by NASDAQ to build a model to predict how the exchange’s plan to move from denomiating shares in sixteenths of a dollar to dividing its dollars into cents would affect trading. According to a report in The Economist, Darley’s predictions were not perfect (his agents traded at larger volumes of shares than real people did), but some of his other forecasts were accurate.

As the amount of data increases, the potential of computer modeling will grow exponentially. “There will be more features and data to estimate various parameters and models with,” LeBaron says. “This is a big plus.”

In the meantime, researchers such as Farmer, LeBaron, and Sunder struggle to find the tools to make their model legitimate, whether they be data or computer power. “The big needs now are in software,” LeBaron says. “I still dream of the ultimate software package to model with and share pieces with others. It doesn’t exist.” Not yet anyway.

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