New Mexico Tech Currency Markets Modeling Project

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Abstract

An overview of the ongoing Currency Markets Modeling Project at New Mexico Institute of Mining and Technology (New Mexico Tech) is presented[1]. The overall model is described, and this paper is an introduction to an ongoing interdisciplinary modeling and simulation effort at the Institute for Complex Additive Systems Analysis at New Mexico Institute of Mining and Technology (aka New Mexico Tech). Findings are summarized, along with specialized software developed for this project. Ongoing efforts, which include modeling of investor herd behavior and investor overreaction to price trends are also outlined.

1. Overview

The Currency Markets Modeling Project has been ongoing at New Mexico Tech for approximately eighteen months. An interdisciplinary team has developed a three-phase model of the currency market price-formation process, which features detailed modeling efforts for order flow, the simulated dealer market, and analysis of simulated price outputs.

The initial motivation of the model was assessment of the impact(s) of trader behavior on prices and bid-ask spreads, and we continue to explore those issues. At this point, we have a functional, complex model of the overall process generally summarized in Fig. 1.

We have developed detailed computer simulation models for investor/trader decision making (in the case of speculative trading) that generates order flow, the interbank dealer market where prices and bid-ask spreads are determined, and the exchange rate time series output of the process.

This paper describes the development of the overall model, which occurred between September, 2002 and September, 2003. The effort has been ongoing, and recent additional funding will enable the development of more sophisticated order flow generation models that include traders who exhibit herding and other behaviors that may not be associated with maximization of expected utility.

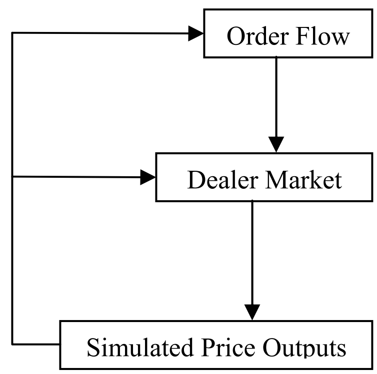

Fig. 1: The basic modeling components of the project.

2. Order Flow

Currency traders – generators of order flow that is external to the actual market mechanism – are modeled as either noise traders or speculators, with an order equally likely to have come from either overall trader type [1]. Noise trader activity is simulated on the basis of the magnitude nature of a particular order – whether the order is a buy or sell request – using a Poisson process.

Speculators may be levered or unlevered [1], and are modeled as expected utility maximizers who may adopt any combination of various trend chasing or fundamental-price strategies [2]. Expected utility maximization drives individual investor order flow in the context of a risk tolerance (specified by the modeler) for each investor and computation of a certainty equivalent [3] for the expectation and variance of the price at the next simulated tick. Investors then trade – subject to modeler-imposed constraints on exposure and minimum order size – on the difference between their current position and the

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certainty equivalent for the random variable expected price at the next tick.

In the case of a fundamental price strategy, the model was developed so that the modeler may select the fundamental price or a lag for the selection of the fundamental price (e.g., the fundamental price may be the price observed some pre-specified number of ticks prior to the current time).

Fifty ticks and the associated fundamental-price trader order flow (in currency units) are shown below in Fig. 2.

For trend chasers, the modeler may specify the number of ticks to be used in development of a two-outcome lottery [3] for the next price. In this situation, the model considers the number of up and down ticks and the average return for both scenarios. Probabilities for up and down scenarios are simply computed based on the proportion of up and down return movements within the preceding return time series.

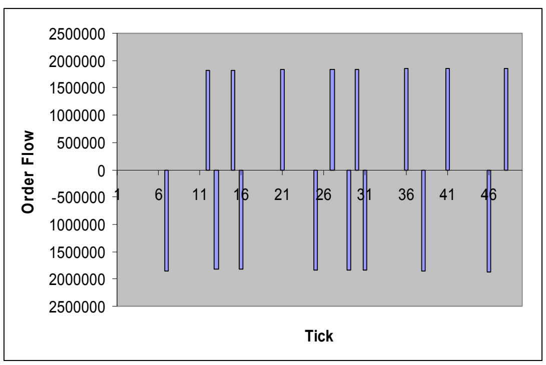

Fig. 2: Fundamental-price trader order flow – with a moving fundamental price window – over fifty observed ticks.

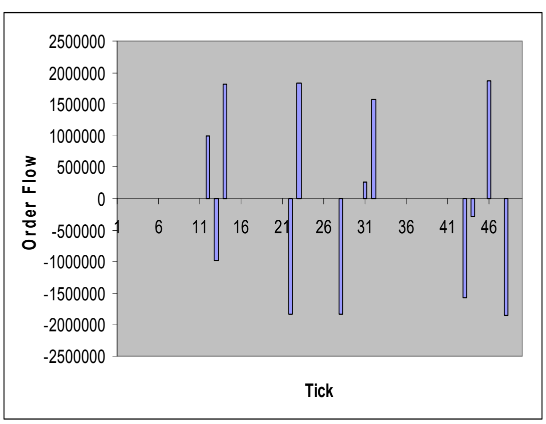

Fig. 3: Trend-chaser order flow over the same interval, and with the same risk tolerance and exposure limit as the simulated fundamental-price trader depicted in Fig. 2.

Fig. 3 contains order-flow data for a trend chaser with a 20-tick time horizon over the same fifty ticks and the same risk tolerance and maximum exposure as the fundamental-price trader whose order flow is depicted in Fig. 2.

The modeler may specify the strategy mixture for any investor; simulated order flow may come from investors pursuing any combination of the two strategies.

The fairly sophisticated investors in this model therefore rebalance their portfolios – subject to externally-imposed constraints – after each simulated tick. Order Flow generated by the trader model enters the separate dealer model, and model-generated prices reenter the overall picture as “new” ticks – or observed actual exchange prices.

3. The Dealer Model

Individual dealer trading strategies and behavior – and, in the aggregate, exchange rates – are impacted by the order flow from traders and individual dealer inventory positions and inventory management policies. Simulated dealers are free to trade at any time via either the simulated electronic limit order book or with any other dealer. Order flow has high information content with respect to macroeconomic factors, and the simulated double auction market generates both bid and ask prices, thereby generating a dynamic spread simulating what is observed in currency markets.

Dealers have no incentive to speculate and are not permitted to speculate in this model. Their profits are generated by buying and selling the single currency based on order flow and existing inventory given the simulated spread at the time of the trade(s). Actual prices and price – and spread – changes are observed as a result of dealer trading behavior, which is governed by a multi-parameter model simulating inventory control policy for each dealer.

Each dealer behaves strategically – though not necessarily rationally – and trades asynchronously (independent of other dealers’ market or limit orders). The price-formation process takes place with a double auction mechanism with a limit order book, and prices are a consequence of transactions happening when buy and sell orders are matched.

Fig. 4 contains an example of simulated exchange rates vis-à-vis a base currency. This plot, as well as Fig. 5 below, was generated solely from simulated random noise trading.

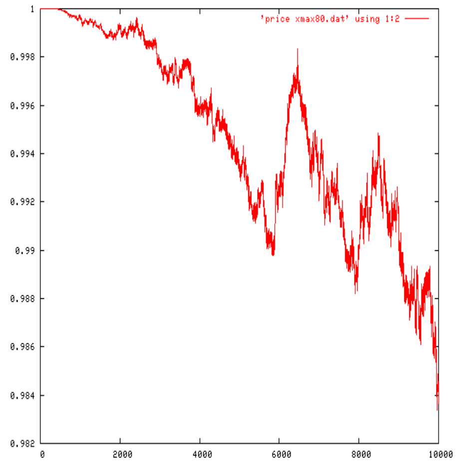

Fig. 4: Simulated exchange rate prices with randomly-generated noise trading.

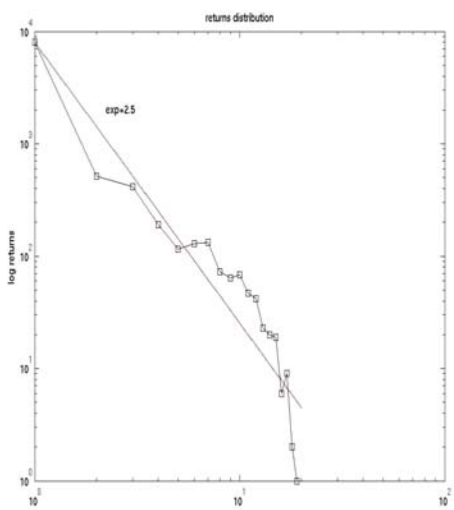

Fig. 5: Power-Law Return Output from the Dealer Model; Slope = 2.5.

4. Output Analysis

Simulated prices and bid/ask spreads are the output of the model. As may be seen in Fig. 5, the dealer market output distribution corresponds to a power-law distribution with slope 2.5. This corresponds to observed actual data we (and others) have assessed, and provides one basis for the output analysis models developed specifically for this project.

5. Order Flow Results to Date

One major motivation for this modeling effort has been an attempt to link trader strategies with observed order flow. While differences exist between trader order flow when risk tolerances, exposure limits, and minimum order constraints are held constant, at this stage it appears to be difficult – perhaps impossible – to differentiate between the two strategies based on observed order flow. This is due to the fact that very similar order flow can be observed from two traders with dissimilar strategies. This can occur when different strategies are implemented in the context of different risk tolerances and exposure limits.

This unsurprising observation is illustrated in Fig. 6, in which order flow from the trend-chasing trader in Fig. 3 is shown. The differences between Fig. 3 and Fig. 6 is the trader's risk tolerance was increased from 0.1 million to 1 million.

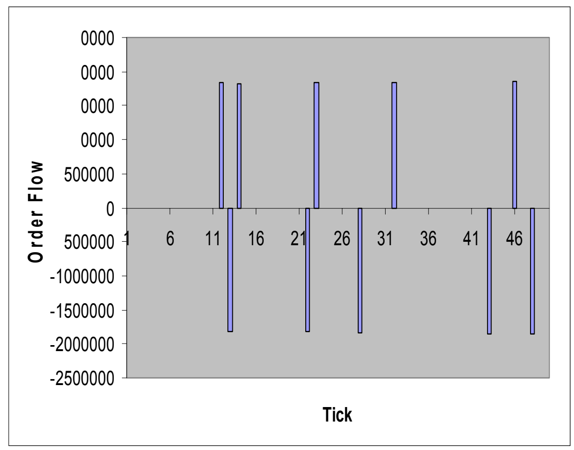

Fig. 6: Order Flow from the Trend-Chasing Trader from Fig. 3, with the trader risk tolerance increased by a factor of 10.

6. Dealer Market Results to Date

The three key parameters in the simulated dealer market are inventory position constraints, sensitivity to overall order flow (that is, the sensitivity to short-term trends in order flow, such as a rash of sell orders), and the degree to which inter-dealer trading is permitted for individual dealers are easily manipulated by the modeler.

Currency-exchange dealer markets are notable for, among other features, their lack of relative transparency with respect to other financial markets. Because of this, model validation has been done in the context of the power-law nature of model output and the fact that changes in model parameters result in outputs that reflect fundamental relationships between bid-ask spreads and price trends.

Not surprisingly, price and bid-ask spread outcomes are sensitive to model parameters and, to an extent that is sensitive to parameter settings, order flow trends. We continue to analyze and modify this model, which is the engine of the overall modeling effort.

7. Output Analysis Results

The key output variables of interest from the perspective of the initial motivation for the study are contagion across and clustered volatility within simulated (and, ultimately, actual) return streams.

We are in the process of development of a contagion-analysis model that is an extension of linear-correlation based methods [4] and are based on nonparametric methods [5] and the theory and methodology of copulas [6].

In order to analyze clustered volatility, we developed a new methodology based on a synthesis of existing theories and techniques [7]. Associated with this effort has been development of a proprietary software package, *Volatility Analyst*, that automates the clustered volatility detection and prediction process [8].

The clustered volatility detection and prediction program is grounded in machine learning techniques, and represents a synthesis of ideas from statistics, electrical engineering, and computer science. To this point, the methodology has proved extremely accurate with respect to detection and simulated real-time prediction of simulated volatility bursts in return data time series.

8. Extensions of the Modeling and Analysis Effort

The major areas for near-term extensions of the modeling effort are order flow generation and output analysis. We will also continue to update and modify the dealer model.

Modification of the order flow generation model will include modification of the expected utility maximization model to include simulated traders who behave in a manner that is not objectively rational.

The first extension area is incorporation of herding behavior [9][10] into our order flow generation model. The notion of herd behavior as an explanation for many observed phenomena in financial markets has been suggested by many, and our model provides a testbed for analysis of alternative herding formulations and different simulated levels of herding and their impacts on simulated prices and bid-ask spreads.

The second extension of the order flow model is incorporation of ideas from behavioral finance [11][12], which are generally contrary to the idea of expected utility maximization as the driving force behind trading behavior [12].

The output analysis effort is currently being extended from the current status as a comprehensive clustered volatility analysis and prediction package with application to a single time series to the multiple time series case. This will include assessment (and, we hope, prediction of contagion and other distribution-tail dependencies) in addition to measurements of cross-time series clustered volatility.

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