Quantitative Results for a Qualitative Investor Model – A Hybrid Multi-Agent Model with Social Investors

Stephen Chen, Brenda Spotton Visano, and Michael Lui

***Abstract*—A standard means of testing an economic/financial model is to see if its simulation can reproduce quantitatively observed phenomena. It is generally easier to produce quantitative results from quantitative models, so qualitative models are often less highly regarded – they are more difficult to test and verify. The hypothesis that social investors played a key role during the recent internet bubble is an example of qualitative modelling that is intuitively viable but impractical to test directly. Building from an established multi-agent model that accurately reproduces quantitatively observed market returns, a hybrid multi-agent model is developed which adds social investors. When the social investors in the hybrid multi-agent model are given a similar market weighting to that which social investors are believed to have had during the recent internet bubble, the model developed here also produces a price bubble.**

***Index Terms*—hybrid multi-agent model, market manias, price bubbles, social investors**

I. Introduction

Multi-agent models can be used to model and simulate many complex behaviours. Agent behaviours can be dictated by tractable mathematical equations or by more arbitrary decision rules. The resulting multi-agent models can subsequently be used to observe the effects of behaviours that are quantitative or qualitative in nature.

An example of a quantitative multi-agent model is the Lux and Marchesi [1]–[3] model of financial markets. The goal of this model is to replicate the observed kurtosis in financial market returns. The agents in this model simulate the behaviours of fundamentals-based and momentum-based investment strategies. Since the market returns/price fluctuations in their model replicate the observed kurtosis present in real financial markets, this quantitative result supports the modelling assumptions of two investor classes (i.e., fundamentalists and chartists) and their specified behaviours.

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S. Chen is with the School of Information Technology, York University, Toronto, ON M3J 1P3 Canada (phone: 416-736-2100 x:30526; fax: 416-736-5287; e-mail: sychen@yorku.ca).

B. Spotton Visano is with the School of Public Policy and Administration and the Department of Economics, York University, Toronto, ON M3J 1P3 Canada (spotton@yorku.ca).

M. Lui is with the Department of Physics, York University, Toronto, ON M3J 1P3 Canada (mlui@yorku.ca).

Market participants are, in the above model, driven by profit motives, and they follow investment strategies based on prices and price expectations. This representation reflects the dominant view of contemporary financial theories that market participants act on objective, market-based information. The substantial emphasis placed on these analytical factors which ground mathematical models of financial phenomena may obscure to theoretical detriment the role opinion and emotion can play in moving the market.

There are times when such qualitative factors may in fact dominate market behaviour and the investment activity becomes “trendy”. In such times, market participation becomes based more on subjective, socially-based reasons than on objective, market-based reasons. Yet, qualitative models incorporating such subjective influences have been for some time less well received in scholarly and industry circles. This resistance may be due in part to the difficulty of replicating the market’s transformation of these qualitative influences into observable quantitative results.

The following hybrid multi-agent model offers a way of capturing such a transformation – the multi-agent model as we employ it here produces quantitative results for a qualitative investor model. The foundation of our model is a discrete implementation of the Lux and Marchesi model. To this stable, quantitatively accurate model, a new class of social investors is added. The specific number of new social investor agents that are added is selected to make their overall influence in the model approximately equal to that of the observed proportion of on-line investors during the recent internet stock bubble [4]. The subsequent model dynamics exhibit a sudden surge in prices (e.g., an asset bubble) followed by a rapid decline that undershoots the fundamental price (e.g., a crash).

Although it is intuitively obvious that a group of investors disinterested in the fundamental price of an asset can move the price for that asset away from its fundamental price, it is not clear how far or for how long such a price movement can occur. The qualitative nature of these non-traditional investment strategies makes it difficult to obtain convincing quantitative evidence to support their validity or accuracy or both. The hybrid multi-agent model developed here incorporates investors with both quantitative and qualitative investment strategies, and the subsequent market simulation provides novel support for the hypothesis that social investors enabled by on-line trading played a key role in the internet stock bubble.

The development of this result begins in section II with a

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background on financial markets that introduces the key concepts of fundamental values, noise trading, and social investors. Our implementation of the Lux and Marchesi model is presented in section III, and a discrete implementation of this model is presented in section IV. Social investors are added to create a hybrid multi-agent model in section V, and the resulting market dynamics are discussed in section VI. Lastly, the paper concludes with a summary of the results in section VII.

II. BACKGROUND

In conventional models of prices in competitive financial markets, the price of equities reflects fully and accurately the existing information on the income earning potential of an asset. This "efficient market" outcome as explored by Fama [5]-[8] suggests that the present discounted value of the expected future income over the life of the asset—its "fundamental value"—will ultimately govern the asset's market price. Deviations from this so-called "fundamental value" will only be temporary – speculators capable of estimating the true fundamental value will quickly arbitrage away any implicit capital gains.

Although intuitively appealing and consistent with a long-standing tradition in finance that acknowledges the importance of "value investing" [9], actual price movements and the resulting distribution of returns do not appear to adhere to the strict predictions of the efficient markets hypothesis. Explanations for persistent deviations from estimated fundamental values include various explanations for a "bubble" in stock prices. A bubble occurs when competitive bidding, motivated by repetitive and self-fulfilling expectations of capital gains, drives up a given asset's price in excess of what would otherwise be warranted by a fundamental value. In one class of models with short trading horizons, the bubble may be driven by the presence of "noise" traders (i.e., "chartists"). Chartists attempt to exploit short-term momentum in the movement of stock prices, and their actions (e.g., buying when prices are rising, and selling when prices are falling) can exaggerate any movement in prices.

The presence of noise traders alters, however, neither the ultimate equilibrium market price for stocks (as fixed by the fundamental value of the underlying assets) nor the fact that the market will eventually reach it. In the extant literature, the formal introduction of "noise" traders creates a mean-reverting market dynamic to explain temporary deviations from fundamentals [10], [11]. The presence of noise traders can confound market dynamics to such an extent that under some conditions or for some time, it is profitable for the more sophisticated traders to disregard the intrinsic value of the asset, follow the herd, and thus contribute to the asset bubble that results [12]. It has also been suggested that herding may explain the excess kurtosis observable in high-frequency market data [1].

Since these traders base their decisions solely on objective market information, the more traditional financial models exclude by assumption the possibility that the investment activity may also be a social activity. In situations where individuals are motivated to belong to a group, the possibility of fads, fashions, and other forms of collective behaviour can exist. Spotton Visano [13] suggests that investing in equity markets is not immune from social influences, especially when investors face true uncertainty. Consistent with the early views of financial markets as "voting machines" when the future is uncertain [13], [14], Spotton Visano's result explains the fad and contagion dimensions of investing which relate to Lynch's [15] explanations of the recent internet bubble.

When objective information is incomplete and individuals base investment decisions on social rather than economic information, outcomes become contingent on the collective assessment of the objective situation, and these outcomes are no longer uniquely identifiable independent of this collective opinion. Attempts to model this heterogeneity of investment behaviour and multiplicity of interdependent outcomes render the mathematics so complex as to threaten the tractability of the typical highly aggregated dynamic model. By presenting an opportunity to analyze the effects of different agent behaviours (and especially qualitative behaviours), there are significant potential benefits in using hybrid multi-agent models to simulate the actions of a financial market.

III. THE LUX AND MARCHESI MODEL

Lux and Marchesi [1]–[3] have developed a multi-agent model that can generate a time series of prices which accurately reflects the returns observed in actual stock markets. The key feature of real-world returns that had been difficult to model previously was the existence of excess kurtosis – compared to a normal distribution of returns, real-world returns are more likely to have unusually large gains and losses. By being able to quantitatively simulate the observed features of real-world returns, this multi-agent model is viewed as a viable explanation for the roles and interactions of multiple investment strategies.

The key features of the Lux and Marchesi model relate to the trading strategies and interactions of two classes of investors. These investor classes include the fundamentalists and the chartists, and the chartists are further divided into two subclasses which represent optimistic chartists and pessimistic chartists. The (aggregate) actions of each investor class lead to a price pressure component, and the subsequent changes in price affect the future actions of the investors. The two key features of the model which allow it to accurately produce simulated prices are the mechanisms which allow investors to switch trading strategies and the method used to specify price changes at any given time step.

An implementation of the Lux and Marchesi model has been developed (further details are provided in [16]). In Fig. 1, the prices observed during 2000 time steps are shown against the total number of chartists (out of 500 total agents). The chartist trading strategy has spikes in popularity which coincide with the periods of exaggerated price volatility. By buying when prices are rising and selling when prices are falling, the actions of the chartists cause a distortion from normally distributed returns. The excess kurtosis of 4.40 in the shown prices is comparable to those originally obtained by Lux [1]. Absent from this version of the model, however, is the sudden surge in prices followed by a rapid decline characteristic of a market bubble.

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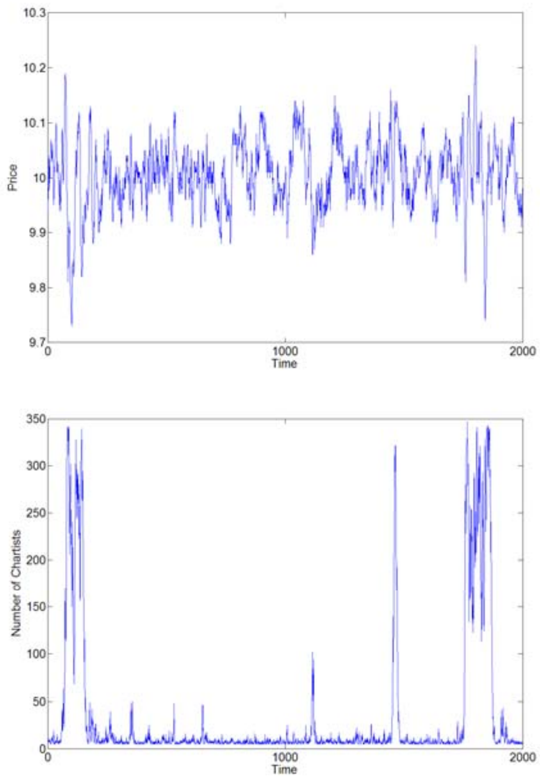

Fig. 1. Deviations from the fundamental value of 10 are exaggerated when a large number of the 500 agents are following the optimistic and pessimistic chartist investment strategies

IV. A Discrete Implementation of the Lux and Marchesi Model

The Lux and Marchesi multi-agent model [1]–[3] is simulated entirely by mathematical equations that describe the aggregate agent behaviour. To develop a market price, this model only needs to know *how many* agents are pursuing the various trading strategies, and not *which* actual agents are in the various states. Thus, the model requires no individual "agents" – it is not a true multi-agent model in the artificial intelligence sense.

The foundation of our hybrid multi-agent model (a model in which some agents are "slaves" to aggregating equations and some agents are independent actors) is a discrete implementation of the Lux and Marchesi model. At each time step of the Lux and Marchesi model, the aggregating equations calculate the number of agents that will change their investment strategy. For example, equation 1 from [1] is shown below:

$$\begin{aligned} \mathrm{d}n_+ / \mathrm{d}t = & \;(n_- p_{+-} - n_+ p_{-+})(1 - n_f / N) \\ & + n_f (n_+ / N) p_{+f} - n_+ (n_f / N) p_{f+} \\ & - (a - b) n_+ \end{aligned} \qquad (1)$$

Equation (1) represents how the number of agents following the optimistic chartist strategy (n_+) changes with time. The first part of the equation represents "mimetic contagion", the second part represents "changes of strategies", and the third part represents "market entry and exit". An example of the effects of the aggregate equations is shown in Fig. 1, but each part of the equations is not always directly programmable in a discrete implementation with individual agents.

To develop an artificial intelligence-style multi-agent model in which each agent has a software state, all transition probabilities p are limited to a range of [0-1]. (We note that the implementation of the original Lux and Marchesi model that we developed in section III occasionally required a negative number of agents to change investment strategies in one of the equation parts in order for the aggregate equations to balance.) Our discrete implementation also assumes that an agent will not change its investment strategy more than once during a single time step. Thus, for each part of the aggregating equations, an integer number of agents is selected (e.g., if 7.7 optimistic chartists are slated to become fundamentalists due to "changes of strategies", seven agents with the optimistic chartist trading strategy will be selected randomly, and then an eighth will be selected with a 70% probability) from the pool of agents that existed at the end of the previous time step (up to a maximum of all agents of that type switching their investment strategy).

This discrete implementation of the Lux and Marchesi model thus has two phases for each time step. In the first phase, the agent actions are calculated based on the aggregating equations. In the second phase, a discrete number of agents perform actions as directed by the preceding calculations. The subsequent discrete values for the number of agents are then used in the next time step. The price and agent behaviours shown in Fig. 2 confirm the consistency of our discrete implementation with the original Lux and Marchesi model.

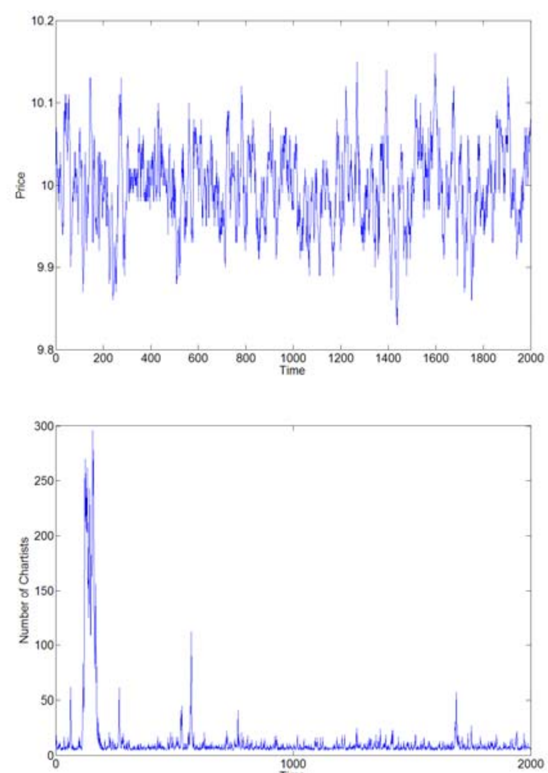

Fig. 2. The discrete implementation of the Lux and Marchesi model produces similar price changes and agent behaviours as the original version shown in Fig. 1. The kurtosis in the shown prices is 2.94

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V. Social Investors and a Hybrid Multi-Agent Model

The previous two classes of "traditional" investors base their decisions on quantitative economic data such as the current market price of the stock, the expected future value of the stock, and the recent rate of change in the observed market prices. To mimic some of the social aspects of investing, we introduce an investor class that bases its decisions on the popularity of the investment activity. Specifically, if a social investor sees a large number of other investors buying, then that social investor will buy as well. Conversely and symmetrically, when the social investor observes a large number of sellers in the market, they will sell.

We distinguish between two types of social investors. "Savvy" social investors randomly sample seven (7) traditional investors – both fundamentalists and chartists – and record the difference between the number of buyers and the number of sellers. If this difference in the observed participation of traditional investors matches or exceeds a social investor's threshold (randomly selected from a uniform distribution from 1-5 for each agent), then that social investor will have an inclination to buy. Conversely, if the number of sellers exceeds the number of buyers by the same threshold, that same investor will have an inclination to sell. A difference of less than the specific threshold for a given social investor in either direction causes that agent to perform no action during that time step.

"Naïve" social investors are similar to savvy social investors in the decision process and their choice of decision criteria. However, rather than sampling traditional investors, they examine a random sample of seven (7) other social investors – both savvy and naïve.

The programmed responses for the software agents attempt to capture several qualitative behaviours of social investors. The thresholds for each agent mimic the effects of peer pressure – some people/agents are easily swayed while others require greater persuasion. The "savvy" and "naïve" agents represent the "trend setters" and the "trend followers" often found in social groups. We saw this, for example, during the recent internet bubble with many new investors following business programs, such as CNBC, for the first time. Still others joined investment clubs for the first time, seeking and receiving investment advice, often from other new investors. Lastly, to simulate the emotional commitment involved with joining a fad, social investors cannot switch their investment decision (e.g., from buying to selling) for 50 time steps – a social investor who sees a large number of sellers but who has bought within 50 time steps will instead perform no action during that time step.

The resulting hybrid multi-agent model has two components. The first is a set of "simulated" agents that are controlled by the aggregating mathematical equations developed by Lux and Marchesi. The second is a set of independent agents whose actions affect the state variables used in the previous mathematical equations. The overall system thus benefits from being able to model and measure the effects of both collective, quantitative behaviours and individual, qualitative behaviours.

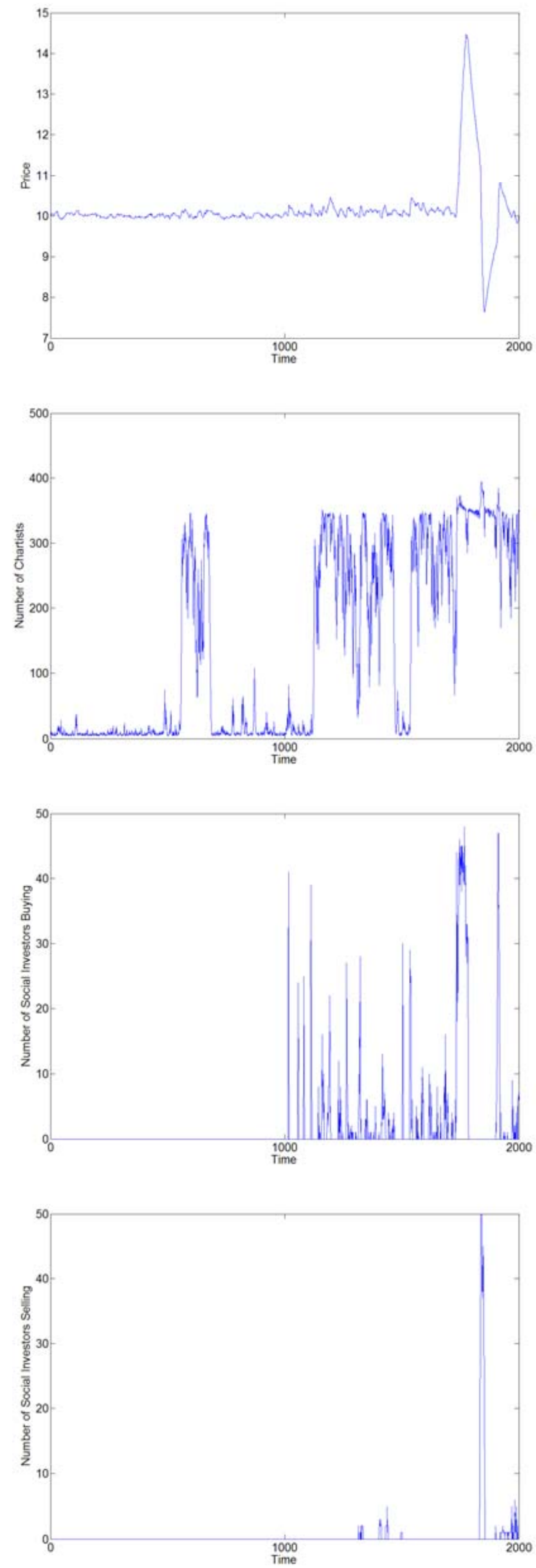

Fig. 3. A small number of social investors is capable of destabilizing the Lux and Marchesi model. The introduction of 50 social investors (10 savvy and 40 naïve) after 1000 time steps leads to greater uncertainty in the market as evidenced by the sustained popularity of the chartist investment strategies (versus the fundamentalist strategy). However, the price bubble (see top chart) does not occur without the sustained buying interest of the social investors (see third chart from top)

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The effects of introducing social investors into a previously stable financial market simulation are shown in Fig. 3. The model starts as the discrete version of the Lux and Marchesi model for the first 1000 time steps. After 1000 time steps, the social investors become active – similar to the introduction of the internet and on-line investing in the 1990's. The effects of social investors in the hybrid multi-agent model create a price chart that leaves the previously stable range to the upside and to the downside – similar to a market bubble and the subsequent crash.

VI. Discussion

The developed hybrid multi-agent model enables a clear differentiation among "social investors", "chartists", and "fundamentalists" and their associated investment strategies. This differentiation leads to a clear demonstration of how expanding or shrinking participation resulting from social investment activities differs importantly in market effects from the "herding" represented by the inclusion of a chartist class. Chartists are usually very sophisticated investors who may use charts and technical analysis to exploit (short-term) price changes. While these price changes motivate herding by chartists that then result in further price changes and deviations from an asset's fundamental value, such models do not explain well the extreme surges and rapid declines of asset prices characteristic of a market bubble.

The effects of an influx of social investors have been discussed qualitatively with respect to the recent internet bubble (e.g., [13], [15]), and a recent analysis of on-line trading data from 1995-2000 suggests that on-line traders invested almost entirely in NASDAQ stocks and owned approximately 10% of the NASDAQ market capitalization [4]. We hypothesize that these types of increases in market participation are an important feature associated with market manias and bubbles. We further hypothesize that a significant portion of the new market participants will be less informed investors – investors who have little understanding of economic fundamentals and their relationship to stock prices.

To examine these hypotheses, we have built a hybrid multi-agent model in which these economically less informed investors have been modelled as social investors. Distinct from traditional investors, the popularity of the investment activity is the exclusive motivator of a social investor's decision to invest. The dynamic effects of adding this new class of social investors into a stable and quantitatively accurate model of traditional investors (i.e., fundamentalists and chartists) can then be observed. In the (discrete) Lux and Marchesi model, there are 500 traditional investors, and 50 additional social investors (10 savvy and 40 naïve) are added in the hybrid multi-agent model. Thus, the social investors in the final model have a similar market weight as the on-line investors did during the internet bubble as calculated by [4]. In the performed simulation, the addition of these social investors leads to a price chart that includes overshoots to the upside and the downside. The quantitative features of this result (e.g., the market weighting of the social investors) provide novel support for the role of social investors during the recent internet bubble.

VII. Conclusion

It is intuitively obvious that a group of investors disinterested in the fundamental price of an asset can move the price for that asset away from its fundamental price. However, the qualitative nature of the above explanation with respect to the role of on-line traders and social investors during the internet bubble creates the questions of how much influence did these new investors have, and was this influence sufficient to destabilize a financial market. Recent results suggest that social investors may have owned 10% of the NASDAQ's market capitalization during the internet bubble, and the presented results show that the addition of a similar number of social investors can destabilize a quantitatively accurate model of a financial market.

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