**Trading Dynamics between Informed and Noise Traders**

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**Project Summary**

The well established hypothesis that market is efficient argues that stock price at any instant of time reflects all the information regarding the firm. If there is favourable news (e.g. the firm beats the consensus profit forecasts) the firm’s stock price quickly goes up to reflect this piece of information. If the firm defaults on the debt, its stock price plummets immediately. It is this feature of the stock price that makes it naturally a signal to reflect the CEO’s capability. In other words, stock prices can be viewed as the “output” of CEOs. This is also the reason that equity-based incentives have become a critical part of a CEO’s compensation package in the past decade.

 However, equity-based incentives can only be effective when the stock price truly reflects the effort level of the CEO. This leads to the fundamental issue: how can one ascertain that stock price is truly informative if the market itself is composed of a huge amount of traders with heterogeneous beliefs? The market microstructure theory says the investors can generally be divided into two lots: one with private information, the other engage in trading for liquidity reasons (e.g. urgent need for cash or reasons other than holding private information). The relative force of these two lots therefore determines the price-setting process and the informativeness of the stock price.

 In this proposal we are aimed to investigate the interaction between informed traders and liquidity (noise) traders and attempt to understand what the impact may be if initial condition (proportion of informed traders) varies. Most research efforts have been deriving variables from high-frequency data or SEC 13-f reports as proxy for noise trading and informed trading, respectively. With the conventional approach using econometric analysis, the result is ambiguous. Such ambiguity also corresponds to the mixed predictions by theories. One school of thought suggests higher level of noise trading leads to better price informativeness whereas another school of thought believes otherwise. Our proposed approach, deviating from the traditional approach that relies on conventional econometric models, will be based simulation models. No attempt, to our best knowledge, has been made to uncover the trading dynamics between informed traders and noise traders. The key advantage of using a simulation model is it can overcome the complexity of modelling dynamic interaction among agents; it can also capture the “emerging landscape” at the “macro level” from the local interaction between individual agents. Our proposed method is a breakthrough in the research of the related area and hopefully can shed some light on the following issue:

1. How the simulation results stack up against the result from existing theories and other related empirical results;
2. The level at which informed trading may result in the closure of the market;
3. How the emerging pattern changes as a result of change in initial condition (e.g. proportion of informed trading in the market, influence of active traders on inactive traders, etc.).

 As our simulation work applies to the trading dynamics within a firm, the result from our proposed research may therefore be extended to several companies by changing the initial proportion of informed trading that fits the company of interest. This may helps us understand the overall dynamics better across firms. The result may also be used to evaluate the link between the stock price informativeness and the optimal CEO incentive contract.

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**Project Description**

1. **Problem Statement**

Financial economists who want to carry out an empirical test on the hypothesis generally resort to econometric analysis so that the significance of the variables of interest can be identified or some kind of causality between variables can be hoped to tease out. Though the testing model is straightforward, the result is static: no dynamics between variables can be captured by econometric models. Also importantly, when nonlinearity is involved in estimating variables using econometric models researchers’ choice of function can be arbitrary. Limitations of popular econometric analysis are all the more obvious when the researchers intend to investigate the dynamic relationship of economic agents.

 In our proposed research our aim is to understand the relationship between informed traders and uninformed (noise) traders and its dynamics. Theoretical framework has been established by market microstructure works such as Grossman and Stiglitz (1980) and Kyle (1985), but most parameters in the market can only be proxied by variables that may be contaminated with high measurement errors. For example, the identification of informed traders and noise traders poses a serious issue to interested researchers. To characterize and measure how informed traders and noise traders interact with each other becomes an even more daunting job.

 The better clarification of this issue has a profound impact in many aspects of our financial world. For instance, the current agenda includes how the dynamics between informed traders and noise traders affect the stock price informativeness. Does more informed trading really lead to better price signal? To what extent that dominant force of informed trading will force the market to close-down due to high asymmetrical information? How does the level of stock informativeness affect CEO incentive contracts? And how does the total trading profits change with the increase of informed traders. Some of the above questions are related to the quality of financial market, some are related to the real economic benefit/cost the whole society should consider. We do not claim to attempt to provide answers to all the above questions. Rather, we propose to use simulation technique to get around the difficulties traditional econometric method is facing in an attempt to investigate the dynamic relationship between informed traders and uninformed traders.

 The simulation method we propose to use is cellular automata (CA). Recently CA has been widely used to understand the emergence of properties from local interaction in the field of social science. By using CA to model interaction of agents, researchers construct a world in which the space where each agent acts is represented by a grid, time advances by steps and a set of rules are used to determine each cell’s (agent’s ) state from its own previous one and those of its immediate neighbours. In our proposed research on the dynamics between two agents: informed traders and noise traders, CA serves the purpose of understanding what the market landscape would be like as our initial condition of the proportion of informed traders varies. Our CA-type modelling requires relatively little computation costs compared with other simulation models such as multi-agent-based or machine-learning-based techniques but can effectively reveal the clusters of informed traders that may arise as a result of the interaction with noise traders.

 We focus on the trading dynamics within a firm and each trader can determine to buy, sell or hold the firm’s stock at each time step. We devise two designs that allow for different motivations of trading. The first one captures the stochastic behaviour between traders by making noise traders be influence by neighbouring informed traders subject to some probability at each time step as per Bartolozzi and Thomas (2006). In the second design noise traders and informed traders act according to their own payoff functions. We assume informed traders incur information gathering costs to get their prediction of firm value correct and noise traders may react to trade with informed traders or other active traders. This design captures the phenomenon where investors tend to follow the “Smart Money”. Once the clusters take shape, whether it is due to stochastic behaviour or innate incentives, the stock’s price can be swayed more by these clusters than by individual investors. We will be able to observe how the “emerging patterns” look like due to the change of parameters.

 Our simulation approach may not be able to answer all the questions we pose earlier such as how much improvement of stock price informativeness can be gained in the presence of high level of informed trading or how can it be linked to optimal CEO incentive contracts, the approach we adopt will no doubt shed some light on the following issues:

1. How the simulation results stack up against the result from existing theories and other related empirical results;
2. The level at which informed trading may result in the closure of the market;
3. How the emerging pattern changes as a result of change in initial condition (e.g. proportion of informed trading in the market, influence of active traders on inactive traders, etc.).
4. **Summary of related research literature**

In this section we discuss related research efforts in financial economic and CA literature:

* 1. **Financial economic literature:**

A key question in agency theory is how risk and information shape incentive contracts. In the seminal theories of Holmstrom (1979) and Holmstrom and Milgrom (1987), the optimal compensation weight placed on the CEO’s output, as a signal of her effort, depends on the “signal-to-noise” ratio. Generally, the argument is that an increase in risk reduces the signal-to-noise ratio while more information about the CEO’s actions increases the ratio. The natural prediction is that pay-for-performance sensitivity (PPS) of CEO’s incentive-based compensation should be decreasing in riskiness of the output since output is a noisier measure of effort in riskier environments. On the contrary, if there is greater information about the CEO’s actions in the output, PPS should be higher.

 Empirically, a firm’s stock price normally serves as a natural measure of the CEO’s output. Consequently, in situations where the firm’s stock price is noisier, PPS should be lower; on the other hand, in situations where the firm’s stock price is more informative, PPS should be higher. Though the logic seems flow smoothly, the implication for stock-based incentive contracting due to the trade-off between noise and information is ambiguous. Before we discuss how this ambiguity arises in empirical work, we should point out the major sticking point is the “interdependence” of noise and information in the literature.

In the classical framework of Grossman and Stiglitz (1980) and Kyle (1985), a sufficient amount of noise trading (also known as liquidity trading) is necessary to give informed investors an incentive to drive prices towards efficiency. That is, informed investors prey on uninformed counterparts and make trading profits at the expense of the unsophisticatedness of the latter. Holmstrom and Tirole (1993) show how greater stock liquidity due to uniformed traders attracts more informed traders who trade on private information. In equilibrium, this greater information-based trading results in greater stock price informativeness (and hence *higher* PPS).

 However, Calcagno and Heider (2007) show that having multiple informed traders and reducing the horizon of the informed traders can result in equilibria where greater stock liquidity reduces stock price informativenss. Stock price informativeness goes down because the increase in uninformed trading (noise) dominates the increase in informed trading (information). This result implies *lower* PPS because of dominant force of noise.

In our proposed research, we do not intend to resolve the relationship between stock price informativeness and PPS. Rather, we would like to investigate the link between information/noise and stock informativeness. As mentioned earlier, the judge is still out over the impact of relative force between informed trading and uninformed trading on price informativenss and to our best knowledge there is no comprehensive empirical test yet (until now) to investigate the mixes between the two forms of trade. The sticking point is one can at best assume institutional investors are informed using Thomson 13-f filings database[[1]](#footnote-1) and avail a stock’s turnover rate as a rough proxy for “noise trading”, but such procedure may attract more questions than provide answers. For example, institutional investors are heterogeneous and some may not be active traders; market turnover is far from being a good measure for noise trading because no one can disentangle the noise part from the information part in this measure. Worse still, they are merely static measures and the researcher has no way of knowing the interaction between informed traders and noise traders, which turns out to be the most interesting piece in understanding the dynamic of stock price informativeness. We therefore resort to the simulation method in the hope of shedding some light on this topic.

* 1. **CA literature:**

Axelrod (1995) makes use of CA and investigates how new political actors (e.g. alliances and empires) can emerge from smaller entities (e.g. nations). His argument is borne out by historical events such as the rise and fall of the Roman and Chinese empires and even today’s international political landscape. The process of formation of aggregate actors is the focus of Axelrod’s model. By setting up simple rules and states, an actor may coerce their neighbours and subjugate them at each time step. Axelrod shows that a simple model like his can demonstrate the emergence of clusters acting as political alliances (not simply a collection of individuals but a body that functions as one). The weaker individual entities rarely pick up a fight but when they do, the strongest actors tend to be dragged in. Furthermore, before an eruption of a war, belligerent actors take into account the total wealth of the opposing clusters, rather than the target actor within the cluster.

 Bartolozzi and Thomas (2006) introduce a stochastic CA model for the dynamics of the financial markets. In their setting, the active traders (who buy or sell shares at time *t*) follow a direct percolation dynamics in order to aggregate in networks of information. Their result shows a drastically different emerging pattern in a market crash/bubble state from the one in a normal trading state. In particular, when their herding parameter is low (i.e. a low concentration of active traders on the grid), the active traders will be distributed in small clusters and the information will be extremely split up on the grid. In such case, the frequency of the occurrence of crashes/bubbles is low. With a high concentration of active traders, clusters of the order of a thousand cells are present and consequently extreme events can happen with high frequency. Their model is also able to reproduce most of the stylised aspects of the financial time series (using S&P500 as their benchmark).

 Intriguing as extreme events such as market bubbles and crashes are, for the purpose of our proposed research we focus on the emerging pattern of trading behaviour between informed and uninformed traders at the firm level. In other words, we are concerned about the interaction of informed and liquidity trading within a firm and how the firm’s stock price informativeness improves as we change the dynamics of trading behaviour. The overall quality of market and price discovery process at the macro level is not the focus of the research.

 The payoff designs between strong and weak political actors in Axelrod (1995)’s model will be the central to our design of trading profits for both informed and uninformed traders. As Grossman and Stiglitz (1980) point out that gathering information of a firm is not costless should be compensated for, we set up some simple rules to mimic such payoff. To make our model closer to the reality that noise traders do learn from informed traders by observing the movement of stock price, we set up a parameter to measure the influence of informed traders on uninformed traders *a la* Bartolozzi and Thomas (2006). Details are explained in the Methodology section.

1. **Methodology**
	1. **States of the cell**

All agents trading the same firm’s shares are represented by cells on a two-dimensional grid. The *i*th trader at the discrete time step *t* is characterised by three possible states:

1. Si(t)=+1: the *i*th trader purchases the stock;
2. Si(t)=-1: the *i*th trader sells the stock;
3. Si(t)=0: no action is taken on the side the *i*th trader;

 The first two types are active traders while the third type is inactive trader in our model.

 Traders are only able to interact with their immediate neighbours in the von Neumann neighbourhood (up, down, left, and right). Given today’s hugely interlinked financial markets, it may seem unreasonable to assume one’s trading behaviour is affected by nearby networks. However, such assumption does make sense empirically as recent research shows investors tend to enjoy informational advantage if their location is close to the firm’s operating centre.[[2]](#footnote-2) We specify the interaction of neighbouring traders by the following parameters:

 *ph* : the probability that an active trader can turn one of his inactive neighbours into an active one at the next time step. That is: Si(t)=0 becomes Si(t+1)=$\pm 1$. This simulates the fact that certain information held by an active trader may encourage a potential neighbouring trader to place a buy/sell order.

 *pd* : the probability that an active trader diffuses and so becomes inactive at the next time step due to each of his inactive neighbour. That is: Si(t)=$\pm 1$becomes Si(t+1)=0. This simulates the fact that the active trader may not be able to draw information from her neighbours’ trading behaviour and choose to quit trading next time round.

 *pe* : the probability that an inactive trader decides to trade at the next time step without being influenced by active traders around her: Si(t)=0 becomes Si(t+1)=$\pm 1$.

* 1. **Identification of informed traders**

The above specifies the dynamics between active traders and inactive traders but we have said nothing about how informed traders can be identified yet. To be able to distinguish informed traders from the lot of active traders, we make another assumption that informed traders always predict the true value of the firm. This is in line with the assumption made by Kyle (1985).[[3]](#footnote-3) The implication of this is the sign of trade conducted by the informed traders is absolutely correct.

 The major difference between a normal active trader and an informed trader is their payoff function. We set up a cost *c* incurred by an informed trader to gather valuable information of the firm. Due to the perfect information assumption we just made, informed traders are ensured to make trading profits (πi) large enough to offset the cost incurred since they always bet in the right direction. This is however not the case for other active traders because they are likely to place the wrong bets and make a loss. Another feature of an informed trader is she is not affected by *pd* (the probability of becoming inactive) at all since she will surely trade on her own private information. Therefore in this design, both active and informed traders exert same level of influence on their neighbouring inactive traders (i.e. *ph*), turning her into an active trader (but definitely not an informed trader as she did not incur the information gathering cost at last time step *t-1*). The sign of this inactive trader’s order (buy or sell) is determined by whom she come across in her neighbourhood. The relationship between the informed traders, active traders and inactive traders can be summarised in Figure 1.

**Active Traders**

trade on their own belief about the future value of the firm.

**Informed Traders**

trade on private information about the correct future value of the firm. Information gathering cost *c* is incurred at each time step.

*pd*

*ph*

**Inactive Traders**

with probability *pe* they will spontaneously place buy/sell orders without the influence of active/informed traders.

**Figure 1: The relationship between active traders, informed traders and inactive traders**

* 1. **Clustering**

In our model, both active traders and inactive traders can be viewed as noise traders. At every time step we generate a random number of informed traders on the grid. We investigate the impact of two designs on the final emerging pattern between informed and uninformed traders.

**Design 1: Percolation clustering**

We invoke the percolation method as per Bartolozzi and Thomas (2006). In this framework, the stability of the system is determined by the values of *ph*, *pd* and *pe* as well as the percentage of informed traders and active traders. We set the values of *pd* at 0.05 and*pe* at 0.00001 while we fine tune the parameter *ph*. We expect to see traders start clustering as a sign of information sharing within the same cluster. The number of active should fluctuate through time and clusters of different trading power emerge. Such cluster can be viewed as a network of traders who observe the same signal of the firm value and trade on their private signals.

**Design 2: Wealth-based clustering**

In this design we let informed traders accumulate their trading profits after each time step (note that we hold the information gathering cost fixed in our model due to the economies of scale as the informed traders becomes wealthier). If an inactive trader meets an active (but not informed) trader, she can either trade with the active trader or stay put. If the inactive trader is willing to trade and the active trader puts the same bet as the informed trader, then both the active trader and the inactive trade make a profit; if the inactive trader is willing to trade and the active trade the opposite direction, both the active and the inactive lose money. If the inactive trader stays put, she earns nothing. Each cell (trader) is given a fixed amount of endowment to begin with and in each round the remaining endowment plus the trading profits, if any, will earn a small amount of cash as interest revenue for each trader. The trading profits accrued to each winning trader is the sum of the losses divided by the number of winners. In other words, it’s a zero-sum game. This design uses the basic structure as per Axelrod (1995), but instead of making the “strong” (informed traders in our case) force the “weak” (noise traders) to pay “tribute” in exchange of the protection, we make the noise traders determine whether or not to trade with active traders. There is a chance the noise traders can lose money but that is the risk they have to take, as in the real world. A budget constraint may be introduced to set up a floor how much one trader can lose.

1. **Possible results and implications**

Our two schemes investigate the dynamics of trading from different angles. Design 1 captures the stochastic process that mimics the human uncertainty in decision making whereas Design 2 captures the trend of “following the Smart Money” in the financial world: traders try to follow successful institutional investors as they believe the latter know something they do not know—private information. In both cases, we expect to see the resulting clusters to have greater impact on the market, or more specifically, on the price change of the firm’s stock, than the occasional traders.

 As the emerging pattern will be highly influenced by the initial state conditions, the percentage of informed and active traders, and the initial endowment and perhaps the tightness of budget constraint, in the extreme case where there is high level of *ph,* the stock price tends to move in one direction, resulting in the situation where the stock is either “overbought” or “oversold”. This corresponds to the argument that higher level of asymmetrical information (extremely high proportion of informed traders relative to noise traders here) leads to market close-down because the liquidity quickly dries up. On the other hand, when there is low level of *ph*, the stock is traded by small groups of traders with heterogeneous belief of the movement of price and the stock is highly liquid.

 To work out the price informativeness we will calculate the ratio of number of informed traders to the number of uninformed traders after each round of simulation and derive the distribution by running the simulation for many steps. Generally we believe the higher the ratio of the number of informed traders relative to the number of uninformed (noise) traders the more information compounded in the firm’s stock price, as suggested by Holmstrom and Tirole (1993). But we also note if this ratio is too high (for example, beyond a certain threshold) the stock may be overbought or oversold as we mentioned in the last paragraph. Hence it would be important to work out how high such threshold would be. On the other hand, if the force of noise trading is dominant, we may see expect the stock price becomes less informative, despite the fact that higher noise trading also attract more informed trading. A time-series of fluctuation of the ratio of informed trading relative to noise trading will help us understand the dynamics of the market better.

 Finally, we expect to see the amount of trading profits declines as the cluster of informed traders grows. This should be true in Design 2 because it is by construction a zero-sum game. This also corresponds to the real world where a winning investment strategy will quickly be replicated by the followers and as more and more investors exploit the same strategy, each of who ends up pocketing fewer profits as the abnormal returns reduce (the hedge fund industry is a case in point).

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1. Institutions with more than $100 million of securities under management are required to report to the SEC. [↑](#footnote-ref-1)
2. See Coval and Moskowitz, 2001, The geography of investment: informed trading and asset prices, *Journal of Political Economy*, 109. [↑](#footnote-ref-2)
3. One can deviate from this assumption by introducing the imperfect signal noise as in Holmstrom and Tirole (1993). But we do not believe this will greatly change our simulation result. [↑](#footnote-ref-3)