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Listen to the Signals from an Interactive Agent-Based Model

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Abstract

In this paper, we develop a trading strategy based on the estimated results of an interactive agent-based model. We examine our trading strategy in nine markets proxied by market indices. Our strategy is able to ride the rising trend and avoid declining periods. In addition, our strategy could outperform market index in some financial markets.

Highlights

- We introduce a trading strategy based on the estimated results of an interactive agent-based model.
- Our strategy is able to capture the rising periods and avoid declining periods.
- Our strategy outperform market index in some financial markets.

Keywords: trading strategy, agent-based model, noise traders, fundamentalists, speculative bubbles, heavy tails

JEL code: G7.001

1 Introduction

A trading strategy is a plan consisting of predefined rules used to make trading decisions. Well-known strategies are momentum, pair trading, and buy and hold, etc. For examples, Harris and Yilmaz (2009) developed a momentum trading strategy based on the low frequency trend component of the spot exchange rate. They found that the low frequency momentum trading strategy offers greater directional accuracy, higher returns and Sharpe ratios, lower maximum drawdown and less frequent trading than traditional moving average rules. Cohen and Cabiri (2015) compared returns from the traditional buy and hold strategy to well-known technical oscillators during the period 2007–2012. They found that during bear markets technical oscillators generally produce better gains than the indices, while the opposite occurs during bull markets. Ramos-Requena et al. (2017) presented a new strategy for pair trading selection based on the Hurst exponent of stock market returns.

Heterogeneous agent models (HAMs)¹ which generate stylized facts of financial returns (unpredictability, fat tails, and volatility clustering) have been introduced and developed by several researchers for decades. However, only a few studies focused on applying HAMs to empirical studies. For examples, Boswijk et al. (2007) estimated a dynamic asset pricing model characterized by heterogeneous boundedly rational agents. Their results supported the existence of two expectation regimes, i.e. fundamentalists regime and trend following regime. Baur and Glover (2014) developed and tested empirically several models incorporating heterogeneous expectations of agents, specifically fundamentalists and chartists, for the gold market. Their empirical results showed that both agent types are important in explaining historical gold prices.

In this paper, we extend the estimated results of an interactive agent-based model proposed by Cheng and Kim (2017), providing a trading strategy based on the estimations of their model. Our trading strategy is able to capture some rising periods during the Dot-com Bubble and the Housing Bubble and avoid some declining periods as bubbles burst. Moreover, our trading strategy outperform market index in some financial markets.

The rest of the paper is organized as follows. Section 2 presents the methodology and trading strategy. Section 3 shows the results. Section 4 Concludes.

¹ See, for example, Hommes (2006).

2 Methodology and trading strategy

We adopt the model (Case 1) with t -distributed shock terms from Cheng and Kim (2017) and estimate the key parameters.² Model is briefly reviewed at the Appendix 1.

We set the window size equal to 500 trading days and the interval between each window equal to 20 trading days. Here fundamentalists' eagerness towards profits (α^f), positive-feedback traders' funding rate (r^c), and noise traders' reaction strength (γ) are chosen key parameters. We move the window from January 1983 to September 2015 and estimate the coefficients of chosen key parameter for each window from January 1985 to September 2015. Within the chosen parameters space³, we run the simulations and apply the two-sample Kolmogorov–Smirnov test (KS test) and Anderson–Darling test (AD test) with historical returns as the benchmark for estimating the coefficients of the parameters. Our null hypothesis is that the distribution of asset returns in the simulated data has the same continuous distribution as those for the historical data. We set the confidence interval equal to 95%, and then run 500 trials. We then chose the set of parameters that minimizes the number of trials that reject the null hypothesis.

We develop a trading strategy based on the signals received from the empirical results. From the model simulations, we observe bubbles occurred always as $\alpha^f < 8$ and crashes occurred frequently as $r^c > 0.2$. From the empirical results, we can see that fundamentalists have a significant influence on the market and market tends to be agitated when γ is larger. When we trade, we would like to buy low (i.e., buy when we expect prices going up) and sell high (i.e., sell when we anticipate prices going down). We trade based on the estimations of parameters as follows.

$$\begin{aligned} \text{Buy: } & \alpha^f < 6, r^c < 0.2, 1 < \gamma < 9 \\ \text{Sell: } & \alpha^f > 8, r^c > 0.4, \gamma < 5 \end{aligned} \tag{1}$$

We trade when the market is not agitated and buy (sell) when we expect prices moving up (down), balancing at the end of each moving window.

² For stability of the coefficients of estimated parameters and so on, see Cheng and Kim (2017) section 6.3.

³ See Cheng and Kim (2017) section 5.2, the chosen parameters space were picked based on empirical simulation experiences.

3 Results

We present the results of performance of our trading strategy here.

Based on the estimation results of α^f , r^c , γ in the U.S. equity market as proxied by the Standard & Poor's 500 index (S&P 500), the German equity market as proxied by the Deutsche Boerse AG German Stock Index (DAX), the British equity market as proxied by the Financial Times Stock Exchange 100 Share Index (FTSE 100), the French equity market as proxied by the Cotation Assistée en Continu quarante (CAC 40), the Swiss equity market as proxied by the Swiss Market Index (SMI), the Japan equity market as proxied by the Nikkei Stock Average (Nikkei 225), the Korean equity market as proxied by the Korea Composite Stock Price Index (KOSPI), the China equity market as proxied by the Shanghai Stock Exchange Composite Index (SSE), and the Hong Kong equity market as proxied by the Hang Seng Index (HSI), we trade in these nine markets. The time period covered is January 1985 to September 2015.⁴ We use the S&P 500, DAX, FTSE 100, CAC 40, SMI, Nikkei 225, KOSPI, SSE, HSI adjusted closing price from Bloomberg.

Given information in the previous window, we estimate the key parameter and decide buy or sell index for current window. This procedure is similar to a back-testing process, so the performance of our trading strategy indicate how well this strategy is good at predicting the future.⁵ We could see in Table 1 that our strategy predicts well (larger than 50%) for buy signal, but not that good for sell signal. We trade less when adopting the signals by the AD test compared to the situation when adopting the signals by the KS test. In addition, we could also see that the buy signals by the AD test and the sell signals by the KS test tend to predict better.

Figures 1 provide the cumulative returns of the trading strategy in the nine markets, where we follow the buy signals by the AD test and the sell signals by the KS test. Our trading strategy is able to capture rising periods during the Dot-com Bubble and the Housing Bubble and avoid declining periods as bubbles burst. Moreover, we outperform Nikkei 225 in the Japan market and SSE in the China market. Figures 2 compare the

⁴ The time period covered in different markets vary due to the availability of data from Bloomberg. For instance, the adjusted closing prices for the SSE index are available since 12/19/1990.

⁵ We move the window from January 1983 to September 2015 and estimate the coefficients of chosen key parameter for each window from January 1985 to September 2015.

annualized returns of the trading strategy with risk-free rates and ten year government bond yields in the nine markets.

	S&P 500	DAX	FTSE 100	CAC 40	SMI	Nikkei 225	KOSPI	SSE	HSI
KS test									
Buy signal	266	210	227	161	169	102	138	64	209
Signal Correct	163	130	137	103	107	64	73	34	127
Correct rate	0.613	0.619	0.604	0.640	0.633	0.627	0.529	0.531	0.608
Sell signal	19	19	55	45	48	51	51	63	24
Signal Correct	10	7	21	25	22	26	31	31	6
Correct rate	0.526	0.368	0.382	0.556	0.458	0.510	0.608	0.492	0.25
AD test									
Buy signal	239	182	182	124	161	95	120	22	128
Signal Correct	154	113	108	76	98	61	66	15	85
Correct rate	0.644	0.621	0.593	0.613	0.609	0.642	0.55	0.682	0.664
Sell signal	2	11	33	33	18	16	37	34	6
Signal Correct	1	4	19	14	7	12	24	19	1
Correct rate	0.5	0.364	0.576	0.424	0.389	0.75	0.649	0.559	0.167

Table 1: Statistics for the trading strategy

Figure 1: Cumulative returns of the trading strategy in stock market indexes

S&P 500

DAX

FTSE 100

CAC 40

SMI

Nikkei 225

KOSPI

SSE

HSI

Figure 2: Annualized returns of the trading strategy in stock market indexes

S&P 500

DAX

FTSE 100

CAC 40

SMI

Nikkei 225

KOSPI

SSE

HSI

4 Conclusion

Though HAMs have been widely discussed, only a few works focus on extending HAMs to empirical studies. In this paper, we extend the empirical results of Cheng and Kim (2017), providing a trading strategy based on the estimations of chosen key parameters. Our trading strategy is able to ride the bubbles during rising periods and avoid declining period after bubbles burst. Additionally, our trading strategy outperform market index in some financial markets. Further study will be to make our strategy be more accurate on predicting the declining periods.

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Appendix 1 Model review

In this appendix, we review the model briefly. There is a single stock market that is populated with three types of traders: fundamentalists, positive-feedback traders, and noise traders. All traders in the market are short-sighted and possess beliefs on next period's price for the stock. Fundamentalists believe stock prices will move back to its fundamental values. They form their expected price based on the differences between fundamental value and current market price, $p_{t+1}^f - p_t$, and adjust their expected price each period. The fundamentalists' demand for stock x_t^f and adaptive process p_{t+1}^f are shown in equations (1) and (2).

$$x_t^f = \frac{1}{r^f p_t} \left\{ \exp \left[\frac{\alpha^f (p_{t+1}^f - p_t)}{r^f p_t} - 1 \right] - 1 \right\} \quad (1)$$

$$p_{t+1}^f = p_t + \nu (p_t^* - p_t), \text{ where } p_t^* = p^* + \sum_{i=1}^t \varepsilon_{2,i} \quad (2)$$

where α^f indicates the eagerness of fundamentalists towards profits, r^f is the funding rate fundamentalists face for financing their positions, p^* denotes the initial fundamental value of the stock, ν captures the speed at which fundamentalists expect the market price to move back to fundamental value, and $\varepsilon_{2,i}$ represents the shock terms resulting from changes of policies and rare events.

Positive-feedback traders chase market trends. They form their expected price based on the differences between their previous expected price and current market price, $p_{t+1}^c - p_t$, and adjust their expected price each period. The positive-feedback traders' demand for stock x_t^c and adaptive process p_{t+1}^c are shown in equations (3) and (4).

$$x_t^c = \frac{1}{r^c p_t} \left\{ \exp \left[\frac{\alpha^c (p_{t+1}^c - p_t) + \beta p_{t+1}^c}{r^c p_t} - 1 \right] - 1 \right\} \quad (3)$$

$$p_{t+1}^c = p_t^c + \mu(p_t - p_t^c) \quad (4)$$

where α^c shows positive-feedback traders' eagerness towards profits, β is the coefficient of the wealth effect, and r^c is the funding rate positive-feedback traders pay for financing their positions, μ is the error correction coefficient representing how sensitive positive-feedback traders correct their expected stock price for the next period.

Accumulated noise traders' demand for stock x_t^n is as follows:

$$x_t^n = \gamma \varepsilon_t, \text{ where } \varepsilon_t = \varepsilon_{1,t} + \varepsilon_{2,t} \quad (5)$$

$$\begin{aligned} \varepsilon_{1,t}, \varepsilon_{2,t} \text{ i.i.d.}; E(\varepsilon_{1,t}) = 0; E(\varepsilon_{2,t}) = 0 \\ E(\varepsilon_t) = E(\varepsilon_{1,t}) + E(\varepsilon_{2,t}) = 0 \end{aligned} \quad (6)$$

where γ is the reaction strength of noise traders to noisy information and $\varepsilon_{1,t}$ comes from the demand for the stock from liquidity traders and traders with biased belief or sentiments. $\varepsilon_{1,t}$ is normally distributed, and $\varepsilon_{2,t}$ varies with different probability distributions.

There is a market maker whose role is collecting orders, announcing execution prices, and executing transactions. The market price each period is determined by the demand of the stock:

$$p_{t+1} - p_t = \theta n \left[(1 - \kappa_t - \xi) x_t^f + \kappa_t x_t^c + \xi x_t^n \right] \quad (7)$$

where θ is the market sensitivity corresponding to changes in the demand for stocks, n is the total number of traders in the market, and κ_t reflects the population fraction of positive-feedback traders in the market at each period. Noise traders exist in the market with a fixed weight ξ , and the proportion of fundamentalists in the market equals $1 - \kappa_t - \xi$. The population fractions of fundamentalists and positive-feedback traders are updated each period as follows:

$$\kappa_{t+1} = \frac{1 - \xi}{1 + \exp(\varphi(\pi_t^f - \pi_t^c))}; \pi_t^f = \sum_{i=1}^t x_i^f (p_{t+1} - p_i); \pi_t^c = \sum_{i=1}^t x_i^c (p_{t+1} - p_i)$$

(12)

where φ is the intensity of choice to switch strategies, and $\varphi > 0$. π_i^f, π_i^c are the cumulative profits realized by fundamentalists and positive-feedback traders, respectively, each period.