Chartist Weights and Market Instability: Applications of the Heterogeneous Agent Model in International Stock Markets

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Abstract

This study is the first to apply the Heterogeneous Agent Model (HAM) to analyze the dynamic relationship between chartist weights and volatility clustering, as well as market bubbles in international stock markets. Using a sample of 50 international stock markets from 1996 to 2011, we determined that (1) HAM is significant in most markets, supporting the existence of dynamic agent weight changes. Based on the Threshold HAM, agents may adopt different trading strategies , from momentum to contratian, in terms of different return volatility. (2) Volatility clustering is significantly positively enhanced by chartist weights. (3) Market bubbles are associated with higher chartist weights.

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Keywords: heterogeneous agent model, volatility clustering, chartist, dynamic agent weights, threshold HAM, bubbles

1. Introduction

In the past two decades, financial theory has witnessed a vital paradigmatic change: a shift from a rational representative agent model to a bounded, rational evolutionary, heterogeneous agent modeloriented. Empirical investigations of the characteristic features in financial markets indicate that volatility clustering, excess volatility, temporary bubbles and fat tails in the return distribution are difficult to explain with rational efficient market theory (Pagan, 1996). Moreover, there is ample evidence indicating that people differ in their preferences, knowledge and beliefs in real financial markets (Allen et al. 2006; Alexander 2008; Hong et al., 1999, 2007). For example, Alexander (2008) noted that identical agents fail to take into account the speculative behavior of different agents in the economy and constructed an equilibrium model in which two types of agents have heterogeneous beliefs. Others, such as Shefrin (2001), Scheinkman and Xiong (2003), Dumas et al. (2005), developed an asset pricing model together with a heterogeneous belief factor. Therefore, it is worth addressing how agents' trading behavior will change over time and how investors have heterogeneous beliefs and actions concerning further asset prices in real stock markets.

The purpose of this paper is that first, we investigate the empirical evidence of heterogeneous agent models (HAMs) in equity markets, which vitally extend to international viewpoints.[1] Moreover, we also adopt various types of HAM frameworks, such as relative performance HAMs, and threshold HAMs, for completely empirical

[1] The following question raised concerns about why we make use of the effects of heterogeneous agents on international aggregate stock markets and explores a vital factor affecting these cross-sectional differences of agents' weights. An analysis of this type appears interesting for several reasons. Stock markets at the aggregate country level are clearly both hard to value as well as arbitrage. This follows from the fact that macro data is noisy and that it is difficult to hedge away idiosyncratic shocks at the country level. Therefore, it appears reasonable that heterogeneous shocks affect stock markets in aggregate and not just different subgroups of stocks. As a number of earlier studies deal exclusively with the U.S., some caution is warranted when comparing these results with our findings for international stock markets. The U.S. results themselves are not fully consistent, and it is obvious that our results cannot be consistent with each of the earlier findings. Apart from this, our results suggest that earlier U.S. findings cannot easily be applied to international cross-sectional effects.

analysis, and extend these to incorporate asymmetric effects into the HAMs. Second, we attempt to utilize chartists' weights estimated from HAMs to explain the financial stylized facts, such as volatility clustering. Previous work on HAMs has demonstrated that heterogeneous expectations within the new paradigm of adaptive belief system provide a viable alternative to the representative agent hypothesis (Brock and Hommes, 1997; 1998).[2] The majority of HAM studies have been modeled to fit the established stylized facts using theoretical perspectives and stochastic simulation techniques. Because of the difficulties in estimating the adaptive belief system of agents' behaviors, which is performed using a complex nonlinear approach, the literature on the empirical analysis of HAMs is less developed. Furthermore, few studies stress the useful applications of the estimated agent weights, such as dynamic chartist weights, in explaining stylized facts. Chiarella et al. (2010) consider the heterogeneous agent effects in the CAPM to prove the validity of asset pricing. He and Li (2008) use Monte Carlo simulation to model agent weights in expressing the over(under)-reaction. Huang et al. (2010) utilize HAMs to successfully simulate the orientation of financial bubbles and crises and attempt to demonstrate that chartist weights will result in bubbles.

On the other hand, this paper directly uses the HAMs with real stock data, not simulated results, to ascertain dynamic agent behavior. The greatest advantage of HAMs is that we are able to distinguish two types of agents, as fundamentalists and chartists are assumed to endogenously switch between trading strategies, based on evolutionary belief. In particular, this useful application of HAMs allows us to endogenously detail the dynamic changes between different agents' trading behavior and then investigate whether there is a significant impact of time-varying agent structures on abnormal market features. In doing so, we are able to obtain a more clear

[2] Inspired by the unrealistic assumptions and empirical anomalies regarding the representative agent model, HAM studies have gained momentum over the last decade.

understanding of the advantages in HAMs as well as applications of the estimated dynamic agent weights, especially chartist weights, and their characteristics, such as which market has a great impact from chartists. This strategy also provides detailed insights into the agents' interactive workings in financial markets that can be of importance to both academics and practitioners. We can view our empirical results as complementary to the line of applications for HAM research, providing further empirical predictions of chartist weights in regards to volatility clustering, excess volatility, and bubbles.

Next, we address the key mechanism of chartist weights in HAMs based on the work by Brock and Hommes (1997, 1998), who introduced a simple tractable heterogeneous agent model with two types of agents: fundamentalists and chartists. Fundamentalists believe, in accordance with the EMH, that prices will trend toward their fundamental value. This group believes that the market price will revert to the intrinsic value of an asset and therefore bases expectations on the deviation of the market price from the fundamental value. They will invest in assets that are undervalued and sell assets that are overvalued. Chartists (or trend-followers, technical traders), on the other hand, speculate on the persistence of deviations from the fundamental value. They extrapolate information from previous prices, expecting trends to continue in the same direction. They will buy (sell) when past prices increase (decrease). Moreover, a number of studies also consider agents' behaviors within these two groups as contrarian traders and momentum traders. Therefore, we can recognize two distinct trading behaviors. Fundamentalist behavior is assumed to have a stabilizing effect on market prices, whereas chartists tend to have a destabilizing effect and drive market prices away from the intrinsic value of the asset.

In addition, we believe that the evolutions of bubble process are related to the model structures of HAMs, which can be described by time-varying agent trading weights. The reason is that the more chartists or trend-followers will destabilize the stock market, which results in bubble events, particularly when the stock price is dominated by them.[3] Thus, one of our motivations is to prove that HAMs are applicable for portraying the dynamic behavior of these agents, as well capable of being utilized to directly examine whether the bubbles that have occurred are positively associated with chartist weights. Although a number of studies attempt to explain the formation of a bubble or crash through the dynamic changes of agent weights, they lack statistic tests and use simple eyeball analysis or simulation approaches to address possible relations (Boswijk et al., 2007; De Jong et al., 2009; Huang et al.,2010). For example, Schulmeister (2009) analyzes the interactions between the trading behavior of technical analyses and the fluctuations of the yen/dollar exchange rate and demonstrates that chartist behavior will lead to sudden crashes.

Furthermore, rather than static disagreement settings, HAMs can better describe the dynamic interactions in market participants' behaviors as proxies for heterogeneity. The switching may be based on relative forecast errors (Ter Ellen and Zwinkels, 2010) or on the distance between the actual and fundamental price. In contrast with recent literature that only explores one heterogeneous proposition to calibrate agent behavior, to the best of our best knowledge, there is little research empirically testing more than one HAMs simultaneously as well as extending empirical HAMs in terms of international perspectives. In addition, this research is also inspired by the asymmetric effect (McMillan, 2007), moreover, suggesting that investors will have different reactions when a previous stock return is either positive or negative. We follow

[3] Previous studies point out that the sources of bubbles are uncertainty, destabilizing forces and stabilizing forces that are attributed to irrational agent behavior (Shiller R. J., 2000; Hong and Stein, 2003). For instance, the momentum traders believe that recent price trends will continue, and this positive-feedback trading is forming the up-trend price pattern as well as leading to price deviation far from the fundamental value. Finally, the arbitrage force of fundamental traders will enter the market, resulting in the bursting of the bubble, and the price then reverts to the fundamental value.

McMillan's ideal that investors will adopt distinct transition parameters to incorporate the asymmetric effect into HAMs to obtain realistic empirical results. Finally, to obtain more interesting and meaningful estimated insights, this paper also judges whether the empirical models of various HAMs are reasonably effective in equity markets and compares the different characteristics of the time-varying agent weights with different international equity markets.

On the other hand, in addition to the above-mentioned empirical HAMs, we also discuss another type of empirical HAM together with a threshold-type mechanism developed by Manzan and Westerhoff (2007). The characteristics of the Threshold HAM allow for nonlinear time variation in chartist extrapolation rates depending on different market conditions. That is, chartists may apply momentum trading when the previous price change is smaller than the threshold value, and the opposite behavior when the previous price change is larger than the threshold value. Following this approach, we are able to explore the distinct threshold values in each equity market as well as apply the applications and conditions of markets agents that switch their trading strategies. These types of HAMs can provide us with significant evidence of heterogeneity of expectations, switching between groups and threshold value, in addition to useful information that will allow determination of whether the market is dominated by chartists or fundamentalists through threshold values.

Compared with other econometric regime-switching models, such as Markov switching formulation, the HAMs we applied are estimated with smooth regime-switching regressions, with the distinct regimes representing the expected dynamic market price processes based on each type of agent adaptive behavior. In particular, smooth-transition regime-switching models are estimated by maximized log-likelihood functions, such as the logistic smooth-transition autoregressive (LSTAR) models (Teräsvirta, 1994), and this approach is relatively suitable and tractable for describing dynamic investor behaviors. The time-varying weights of the regimes are then interpretable as the fractions of agents belonging to each type. In addition to stock markets, recent studies have examined estimated asset pricing models, featuring chartists and fundamentalists, for several types of asset prices, including exchange rates (Manzan and Westerhoff, 2007; De Jong et al., 2010), option prices (Frijns et al., 2010), oil prices (Reitz and Slopek, 2009; Ter Ellen and Zwinkels, 2010) and other commodity prices (Reitz and Westerhoff, 2007).

In this paper, we consider stock returns with behavioral heterogeneity and estimate the model using monthly, weekly, and daily data from international stock markets from 1996 to 2011. The estimated results of our model suggest that behavioral heterogeneity is significant and that there are two different regimes, a 'mean-reversion' regime and a 'trend following' regime. Our findings are as follows: (1) HAMs support the existence of dynamic agent weight changes. Based on Threshold HAMs, agents may adopt different trading strategies in terms of different return volatilities. Furthermore, the return prediction of HAMs is better. (2) Volatility clustering is significantly positively enhanced by chartist weights. (3) Market bubbles are associated with higher chartist weights. This paper contributes to the literature in a number of ways. First, we empirically investigate the validity of HAMs in an international viewpoint, the structure of time-varying chartist weights and their predictive power. Second, the financial time series stylized facts, such as excess volatility and volatility clustering, are explainable by chartist weights. Finally, using the chartist weight variation, we can determine the orientation of temporary bubbles. As such, this paper provides and compares interesting insights into the works of different financial markets as well as the effectiveness and applications of HAMs. These comparisons provide vital suggestions to both academics and practitioners.

The remainder of the paper is organized as follows. Section 2 reviews the literature on the empirical frameworks of the various HAMs. Section 3 sets up hypotheses and addresses the data and econometric methodology. Section 4 presents our estimation results and their applications. Section 5 presents the conclusions.

2. HAM Descriptions

In this section, we will develop various stylized heterogeneous agent models that will be used to evaluate the effect of heterogeneous agents on stock prices within international perspectives. The empirical framework of HAMs in this paper is based on the models of Brock and Hommes (1997, 1998), Manzan and Westerhoff (2007), Westerhoff and Reitz (2003: 2005), Reitz and Westerhoff (2007), Reitz and Slopek (2009) and Ellen et al. (2010). Many works on HAMs are very useful as formulations of heterogeneous beliefs in financial markets, such as the stock, exchange rates, options, oil, and commodity markets. Therefore, there are basically three empirical settings of HAMs used to describe nonlinear dynamic systems, and each model emphasizes the distinct propositions or trading strategies in the real market to calibrate the interactions among investors: effective weight model, relative performance model, and threshold dynamic model. On the other hand, plenty of papers argue that investors may have different responses or adopt opposite trading strategies when the previous stock price increases or decreases, as related to the notion of loss aversion. As a result, investors respond more to undervaluation, which leads to the asymmetric effect, i.e., they are more hesitant to sell in cases of overvaluation than to buy in cases of undervaluation (Kahneman and Tversky, 1979). To make the model suitable for estimation, we extended the cited models to consider this asymmetric effect in the HAM. This asymmetric ideal of modeling setting originates from McMillan (2007) and involves modifying the transition functions of the regime-switching model with two states. The underlying assumption of all these models is that there are different types of agents that are not constant over time with heterogeneous expectations active in the market. This is the added value of our model vis-à-vis the traditional HAMs.

The agent groups are divided into fundamentalists and chartists. The demand for stock price for fundamentalists is based on the difference between the price at time t and the expected price at time t+1. $D_t^F = a^F \left[E_t^F(P_{t+1}) - P_t \right]$, where P_t is the log-price in period t, a^F stands for a positive reaction parameter and *E* the expectations operator. Fundamentalist demand will increase when they expect the future price to be higher than the current price and vice versa. The fundamental value is the long-run intrinsic value of stock price, and the price of the asset will revert to the long-run value. This means that fundamentalists expect prices of overvalued assets to decrease, and prices of undervalued assets to increase, until the price of the asset reflects the fundamental value. The expected price can be given by $E_t^F(P_{t+1}) = P_t - b^F(P_t - F_t)$, where F_t is the log-fundamental price in period t. The equation shows that the price movement expected by fundamentalists is caused by the deviation of the price from the fundamental value. A distinction is made of $(P_t - F_t)$. Fundamentalists' reaction to an overvaluation is captured by an expectation of b^F being negative, as fundamentalists will expect the stock price to decrease (increase) when the current price is above (below) the fundamental value. Therefore, we can view fundamentalist trading as a contrarian strategy.

The second group of agents is called chartists (trend-followers or momentum traders). These basic type of chartists are replaced with a more complex and realistic type that use a very simple form of technical analysis to form their expectations about future prices. In line with fundamentalists, chartist demand is linearly conditional to the expected price change, $D_t^C = a^C \left[E_t^C(P_{t+1}) - P_t \right] = a^C \left[P_t - b^C(P_t - P_{t-1}) - P_t \right]$, where a^C denotes a positive reaction parameter. This indicates that demand will rise when chartists expect the future price P_{t+1} to be higher than the current price P_t. Moreover, the question arises of what is the exact functional form of technical analysis is, as it comes in many different forms (Brock et al., 1992). Chartists expect trend movements to continue in the same direction. Therefore, chartists have a destabilizing effect on stock prices in that they extrapolate the current trend irrespective of the level of the fundamental price. As such, consistent with the heterogeneous agent literature, we select a simple technical trading rule that incorporates these characteristics, namely an AR(1) specification. A distinction is made of $(P_t - P_{t-1})$, for an upward or downward trend, and chartists, as a momentum strategy, expect trend movements to continue in the same direction. Therefore, we expect b^C to positive for chartists.

The total market demand for a stock asset consists of the weighted average of the demand of chartists/technical traders and fundamentalists. Then, the price adjustment of the asset depends on the excess demand plus a noise term, which can be expressed as

$$P_{t+1} = P_t + \theta\left[W_t D_t^F + (1 - W_t) D_t^C\right] + \varepsilon_t \tag{1}$$

in which θ is a positive price adjustment parameter governing market frictions, and ε_t is a random noise term. Accordingly, if buying exceeds selling, the price of the stock goes up, and if selling exceeds buying, the price of the stock goes down. The most prominent mechanism in HAMs is the introduction of the distribution of agents over their trading rules changes through time. This means that W_t, called the transition function of agents, is the fraction of fundamentalists in the market, such that $1 - W_t$ is the fraction of chartists in period t. The fundamentalist-chartist approaches can be considered different strategies that agents use to evaluate the market and to make investment decisions. Referring to the literature, we denote that agents choose their strategies based on a relative performance model, W_t^R, and an effective weight model,

W_t^E , as expressed in the following multinomial logistic equations:

$$W_t^R = \left(1+\exp\left(-\gamma\left[\frac{A_t^F - A_t^C}{A_t^F + A_t^C}\right]\right)\right)^{-1}$$
$$A_t^F = -\sum_k^K \left[E_{t-k-1}^F(P_{t-k}) - P_{t-k}\right]^2, A_t^C = -\sum_k^K \left[E_{t-k-1}^C(P_{t-k}) - P_{t-k}\right]^2 \tag{2}$$

$$W_t^E = \left(1+\exp\left(-\gamma\frac{|F_t - P_t|}{\sigma_t}\right)\right)^{-1} \tag{3}$$

Note that both W_t^R or W_t^E are restricted to the interval [0, 1]. W_t^R and W_t^E indicate the fraction of traders that adopt the fundamentalist strategy. The difference is that eq (2) represents the relative performance of either a fundamentalist or chartist trading strategy, whereas eq (3) focuses on the efficient performance of the fundamentalist trading strategy.

As in De Jong et al. (2009), in this paper, the relative performance of a strategy is measured by its past forecasting accuracy. The trading rules are time-varying because of the agent types changes through time. Agents choose between strategies conditional on the squared forecasting error in the previous *K* periods. Thus, A_t^F is the conditional performance of the fundamentalist approach, and A_t^C is the conditional performance of the chartist approach. In contract, eq (3) models that a larger absolute deviation between the price of the asset and its fundamental value is associated with a stronger the confidence in mean reversion. As a result, the market impact of fundamental analysis increases. Parameter γ is the intensity of market participants and represents the extent to which the performance of a certain strategy determines whether it is adopted. With $\gamma \to 0$ ($W_t^R = W_t^E = 0.5$), a strategy that is performing better in period *t* is more broadly applied at time *t+1*, and therefore, the demand of that group will weigh more heavily in period *t+1*. In a situation of $\gamma \rightarrow \infty$ ($W_t^R = W_t^E = 0$ *or* 1), all agents switch to the strategy that was performing best in the preceding period. This sensitivity parameter also can be characterized as the measure of status quo bias, as it governs the reaction speed of traders to profit differences (Kahneman et al. 1991). Moreover, the perceived mispricing in eq (3) is conditioned by the volatility measured by σ_t. Given that the risk of trading increases with volatility, the agents are more cautious in turbulent periods.[4]

To be more specific, the asymmetric aforementioned effect is taken into account in term of the parameter, γ,of the switching function. That is, the response of the agents may be distinct between the rising and falling markets.

$$W_t^R = \left(1 + \exp\left(-\left(\gamma_1 \left[\frac{A_t^F - A_t^C}{A_t^F + A_t^C}\right] I_t\right) - \left(\gamma_2 \left[\frac{A_t^F - A_t^C}{A_t^F + A_t^C}\right](1 - I_t)\right)\right)\right)^{-1}$$

$$W_t^E = \left(1 + \exp\left(-\left(\gamma_1 \frac{|F_t - P_t|}{\sigma_t} I_t\right) - \left(\gamma_2 \frac{|F_t - P_t|}{\sigma_t}(1 - I_t)\right)\right)\right)^{-1}, \ I_t = 1, \ if \ \ r_{t-1} > 0, \ otherwise \tag{4}$$

This transition function thus incorporates momentum threshold behavior, such as by modeling dummy variables into the parameter γ and is further characterized by asymmetry between the regimes of fundamentalist and chartist trading strategies. Finally, substituting equations 2, 3, and 4 into 1, after rewriting we obtain the following set of equations that specify the various full heterogeneous agent models for changes in the price of the stock market between time t and t + 1.

Moreover, we also consider the threshold HAM model proposed by Manzan and Westerhoff (2007), which argues that agents may utilize a contrarian strategy and

[4] Frijns et al. (2010) address that traders have the opportunity to do so, but the frequency at which strategies are actually updated depends on the magnitude of γ. The advantage of the current set up is that it provides the most flexibility in terms of behavior. Furthermore, the fact that individuals can enter and exit the market at any time has an effect on the relative magnitude of the population but not on the distribution of individuals over groups.

momentum strategy in the different market states, which is separated by the return of threshold value. These two states are such that state 1 = $\{P_t - P_{t-1} \le c\}$ and state 2 = $\{P_t - P_{t-1} > c\}$, where c is the previous return of threshold value. In particular, it is assumed that chartists will use different trading strategies in these two states, that is a momentum strategy in a small price variation scenario and a contrarian strategy in a large price change scenario. However, in comparison with previous HAMs, the agent weights of this type of HAM model are fixed, but its advantage is that we are able to determine the return of threshold value when agents will change their trading strategy.

3. Data and Methodology

This section empirically discusses nonlinearities between the two types of agents in international stock prices on the basis of the above theoretical framework. Our empirical methodology belongs to the STAR model family, originally proposed by Teräsvirta (1994).[5] To examine the empirical evidence for the HAM outlined in Section 2, we employ the STAR–GARCH procedure developed by Lundbergh and Teräsvirta (1998). More precisely, our empirical HAM model consists of a mean equation containing a smooth transition variable, as in equation (2), (3), and (4), and a standard GARCH(1,1) volatility equation, as follows. Furthermore, to determine the appropriate delay k of the transition function, the modeling procedure for building STAR models is performed as suggested in Teräsvirta (1994) through either the AIC or BIC criterion, and then, we set $k = 1$. Finally, the empirical process of our HAM models is estimated using a quasi-maximum likelihood approach, and the initial value of

[5] The model has been applied well in financial fields, which reveals that the STAR approach is capable of modeling the nonlinear mean reversion of asset prices. It can also provide superior performance compared with simple ARMA specifications and regime-switching approaches, such as the Markov-switching model.

parameters are set by a grid of value because of the nonlinear model. Our data sample contains the data of 50 countries derived from IMF (International Financial Statistics database) data during 1996 – 2011, including day, weekly and monthly data. The variables include share price, trading volume, and gross national product. The sample period was selected to include bull markets and bear markets and to be long enough to avoid bias. In this paper, our testable hypotheses are:

H.1 The validity of HAMs and dynamic agent weights are significant in international stock markets.

H.2 The stylized facts in stock markets can be explained by chartist weights.

H.3 The bubble is positively related with chartist weights.

4. Results

To obtain more accurate results for empirical verification, the estimated parameters of HAMs, the dynamic chartist weights, and the relevant market quality proxy variables were obtained for standardized conversion. Because the fundamental value is not easy to calculate, this article views the moving average value of asset prices as the proxy variable for market fundamental values. To verify the hypothesis concerning whether a HAM can be developed and applied to a national stock market can be set up, in this research, we examined six type of HAMs as applied to estimated individual market results (basic analysis weight, the weight of technical analysis, relative performance, asymmetric basic analysis weights, weight of asymmetric technical analysis and asymmetric relative performance). In addition, the six HAM models were examined using different data frequencies and with thorough testing with different data. The six HAM results were consistent regardless of frequency. Table 1 lists the HAM parameter empirical results and shows that the investment transactions weight average number relative performance is better than the HAM model results (the

Table 1. The mean value of agents' weights

Country	alpha		beta		rho		Log-likelihood
Argentina	-0.007	(0.91)	0.154	(0.02)	-6.532	(0.39)	-8163.727
Australia	-0.074	(0.82)	0.043	(0.89)	-0.844	(0.90)	-5691.059
Austria	-0.448	(0.09)	0.568	(0.03)	0.368	(0.07)	-7221.374
Belgium	-0.602	(0.04)	0.806	(0.01)	0.279	(0.02)	-6337.762
Canada	0.114	(0.00)	-0.095	(0.00)	29006.460	(0.91)	-6357.938
Chile	0.153	(0.00)	0.244	(0.00)	-105.980	(0.28)	-6174.656
Colombia	-0.473	(0.12)	0.758	(0.01)	-0.403	(0.05)	-6966.441
Czech Republic	-0.032	(0.29)	0.209	(0.00)	4.831	(0.04)	-7262.441
Denmark	-0.604	(0.02)	0.745	(0.00)	0.102	(0.16)	-6162.599
Egypt	-0.168	0.724	0.188	0.693	-15.433	0.856	-13784.960
Finland	-0.796	0.008	0.840	0.005	0.274	0.018	-8431.362
Greece	-0.711	0.010	0.948	0.001	0.191	0.026	-8014.363
Hong Kong	0.075	0.000	-0.065	0.000	27.628	0.146	-8039.887
Hungary	-0.528	0.094	0.633	0.046	0.388	0.086	-8240.365
Iceland	-1.196	0.000	1.197	0.000	-0.358	0.051	-8626.185
India	-0.146	0.614	0.295	0.309	7.876	0.499	-7862.327
Indonesia	0.297	0.380	-0.037	0.913	-2.340	0.663	-7925.805
Ireland	-0.678	0.007	0.784	0.002	0.163	0.045	-7100.645
Israel	4.489	0.000	-4.840	0.000	0.014	0.001	-8584.519
Jordan	-0.558	0.004	1.028	0.000	0.346	0.000	-5661.655
Malaysia	-0.323	0.223	0.271	0.310	-0.728	0.274	-7568.200
United States	0.021	0.080	0.282	0.000	916.757	0.670	-5942.219
New Zealand	-0.041	0.012	0.143	0.000	29.917	0.020	-4899.387
Nigeria	-0.591	0.000	1.314	0.000	-0.423	0.000	-5060.965
Norway	-0.430	0.135	0.454	0.114	0.363	0.179	-7234.103
Pakistan	-0.315	0.298	0.502	0.099	-0.513	0.228	-7815.215
Peru	-0.654	0.001	1.035	0.000	0.233	0.000	-7188.417
Poland	-0.331	0.392	0.364	0.345	-0.080	0.752	-8151.092
Portugal	-1.033	0.015	0.606	0.151	0.401	0.054	-7676.856
Russia	-0.089	0.022	0.389	0.000	-7.186	0.000	-9510.621
Singapore	-0.162	0.594	0.250	0.414	-2.629	0.542	-7263.599
South Africa	0.426	0.296	-0.293	0.472	-1.052	0.413	-6787.347
Sri Lanka	-0.623	0.022	1.058	0.000	0.077	0.089	-6334.333
Sweden	-0.640	0.056	0.679	0.042	0.382	0.069	-7293.158
Switzerland	-0.070	0.000	0.170	0.000	12.495	0.014	-6424.956
Thailand	-0.278	0.367	0.451	0.146	-0.886	0.281	-7872.912
Turkey	-0.460	0.160	0.490	0.133	-0.126	0.428	-9660.474
Taiwan	0.278	0.467	-0.160	0.674	-1.607	0.616	-7432.252
Venezuela	1.027	0.349	-2.475	0.024	1.159	0.150	-11789.640

asymmetric relative performance HAM). Only the relative performance HAM results are shown in Table 1. These results indicate that there are alpha-majority countries with significantly negative fundamentalists where, in the HAM, they enter transactions when market prices deviate from fundamentals, including Greece and Iceland. The values of the other European countries are also relatively large. The results indicate that value of the emerging countries, such as Jordan, Peru and Sri Lanka are significantly positive, but the beta value of European countries is also larger for the beta coefficient. The value of rho (conversion speed) is mostly not significant or negative, which may be related to model theory according to past literature. Analysis of investment in the context of human rights statistics uncovered no consistent results for different countries in terms of support of human rights when comparing U.S. market investors vs. fundamentalist European country investors. Changes in investment in human rights are not a persistently associated with investor trading strategies as indicated by correlation coefficients. Analysis of investment in human rights based on the coefficient of skewness revealed that redistribution is not the norm, as there the value is mostly positive with a partial and low narrow peak.

Based on the empirical results, the relative performance HAM appears to be closer to the real market situation, where different types of investors will select appropriate investment strategies based on past investment performance after taking into account the different types of investors with investment performance in regards to dynamic conversion adjustment, whereas the weight of other basic analysis and technical analysis weighting HAMs only consider the type of investment being converted. Actual estimates are too complex. Thus, to facilitate the comparison of the relative performance HAM (model 2) and non-relative performance HAMs (models 2 and 3), the empirical parameter results, in terms of descriptive statistics, are presented in Tables 2 and Table 3. In addition, when using six weeks of data, monthly data and daily data, the HAM results display little difference. Therefore, this paper presents only a month's worth of empirical results. Table 2 presents the national data estimates for 50 countries using model 1 and 2. In addition, the estimated parameter and statistical data are divided into monthly and daily data. Both monthly and daily data results can be found in Table 2, and the alpha and beta items are consistent with the expectation that the coefficient of the asymmetric model is larger than the original model. In addition, to compare HAM predictive ability, this paper examined the relative performance HAM, the random walk model and GARCH model for the prediction of the next price performance. Ninety percent of the sample period before the estimated sample period was compared in terms of a 10% predictive value away from the sample, with the comparison standards being absolute percentage error (mean absolute percentage error, MAPE) and root mean square error (root mean squared error, RMSE).

Table 2. The summary statistics of agents' weights of model 2.

Monthly data				
	alpha	beta	alpha	beta
Mean	-0.042	0.287	-0.063	0.312
S.D	0.363	0.377	0.334	0.364
Skewness	-0.464	-0.830	-0.620	-0.948
Kurtosis	-0.060	0.309	-0.216	0.123
Min	-0.722	-0.391	-0.764	-0.298
Max	0.888	1.030	0.617	1.002
Daily data				
	alpha	beta	alpha	beta
Mean	-0.033	0.134	-0.148	0.240
S.D	0.849	0.999	0.840	1.008
Skewness	21.824	17.237	22.930	16.699
Kurtosis	4.111	-3.796	4.241	-3.693
Min	-1.033	-4.840	-1.186	-4.780
Max	4.489	1.058	4.409	1.326

Table 3. The significant numbers of parameters of Model 2

Monthly data	Alpha is significantly positive	10	7
	beta is significantly negative	22	28
Daily data	Alpha is significantly positive	18	27
	beta is significantly negative	21	28

Table 4. The predictive power

	Model 2		RW Model	GARCH Model
Monthly data				
MAPE	5.49	5.46	5.86	5.63
RMSE	4.41	4.36	4.56	4.55
Daily data				
MAPE	0.01	0.008	0.018	0.011
RMSE	0.008	0.006	0.012	0.009

The HAM results were more accurate. As hypothesis 1 indicates, the relative performance and the empirical results of for the asymmetric relative performance HAMs are more suited to subsequent research, which allows for an examination of the relative performance and asymmetric relative performance HAMs in the context of the main empirical model. Table 4, which lists the predictive ability of the empirical results, found that regardless of whether month or day data were used, the asymmetric relative performance HAM prediction error was smaller, and the relative performance HAM prediction error had slightly larger error, but there were no significant differences in errors. The HAM predictive ability for future share price is shown in Table 4.

We also investigated a threshold HAM (model 4) using national stock market data. Model parameter estimation collated to 36 significant thresholds, with 18 significantly positive beta 1 values and with 18 significant beta 2 values. Figure 1 shows the national HAM threshold allocation map, with blue for the estimated parameters significantly positive only when meeting the threshold value (converted to kinetic energy trading strategies) and red for estimated parameters that are significantly negative only when the threshold value is met (converted for reverse trading strategies). However, in Figure 1, the threshold value does not display a significant trend or distribution. This article further examines this value in the context of comparing the characteristics of different markets, such as the degree of national development, status as a BRIC emerging country, and region to determine if there is a significant difference.

Figure1. The distribution of threshold value of threshold HAM model

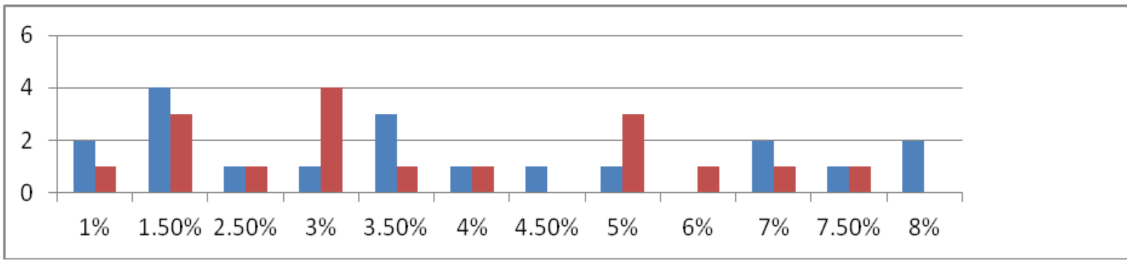


Figure 2. The distribution of threshold value of threshold HAM model in G10

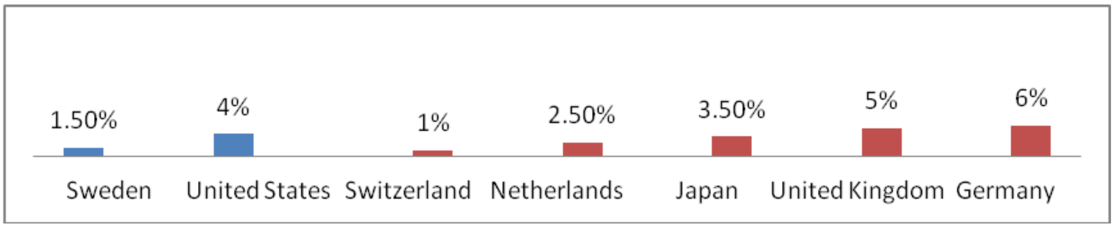
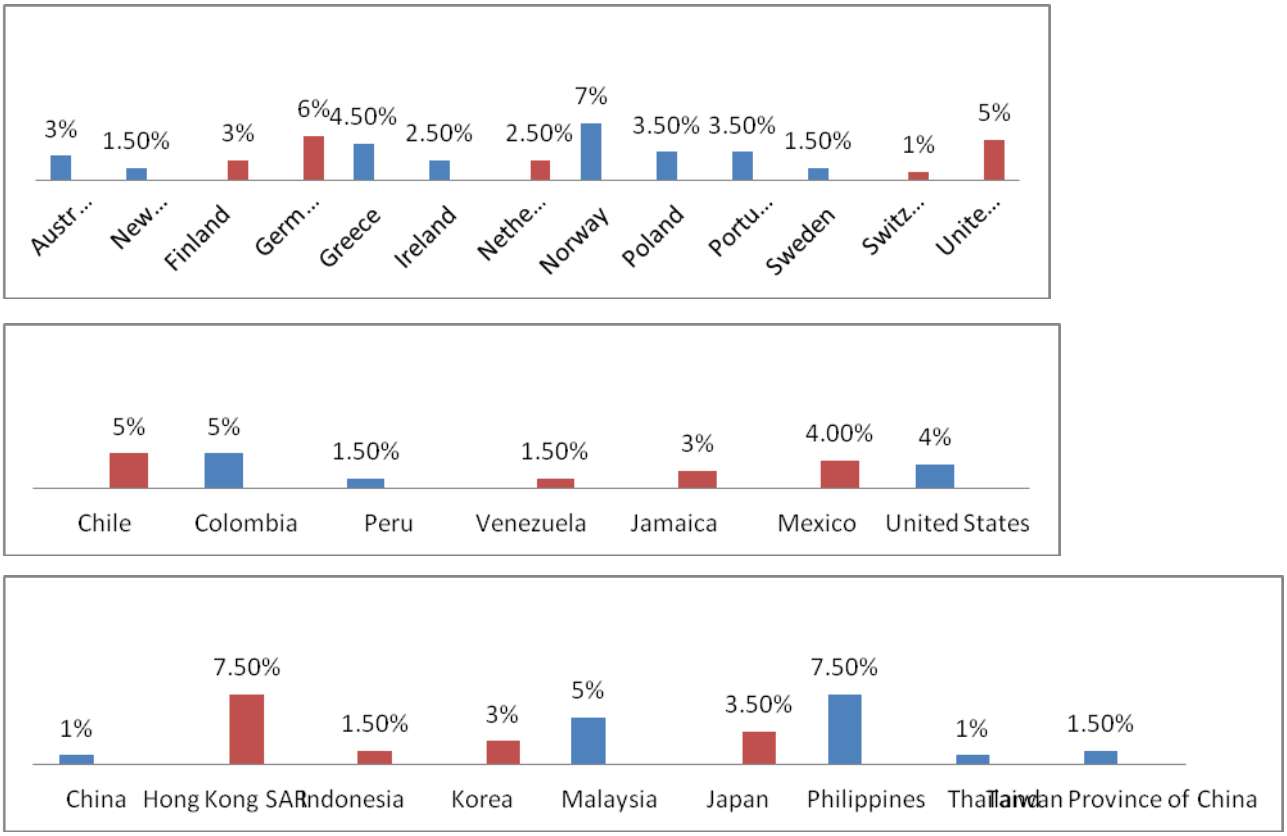


Figure 3. The distribution of threshold value of threshold HAM model in BRIC

(Where blue bars stand for either positive coefficients or thresholds of parameters, and red bars are negative coeffieients.)

Figures 2 and 3 show the degree of development in different countries, and no significant trends of the threshold value were detected. The results are different for the United States, United Kingdom, Japan, and Germany. Among the BRIC countries, only the China and Russia results indicate significant investment in the region involves the kinetic energy strategy, with the market remuneration rate changes of 1% and 2.5%, respectively. At the sub-region level, there is generally no one specifically regional threshold clustering phenomenon, though Taiwan, China and Thailand display more similar investor behaviors. The main significant proportions are as follows: Australia and New Zealand (2/2), Europe (11/20), Central and South America (4/5), North America (3/4), North Asia (1/1), Africa (2/3), West Asia (2/5), South Asia (2/3), and East Asia (9/10). There are still many investment reasons that need to be explored in follow-up studies, such as, for example, changes in exchange rates or trade dependence factors in the model.

Figure 4. The distribution of threshold value of threshold HAM model in different areas.



The empirical results of this paper apply the GARCH model to estimate the conditions of market volatility, with the technical analysis weighting factor (wtc) estimated in the model estimated by each individual market average. The δ average significantly positive technical analysis weighting factor obtained by the relative performance indicator model estimates was δ = 0.603 (2.01) with 32 values significantly positive, and the rest of the values were not significantly negative. The technical analysis weighting factor by asymmetric relative performance indicators model estimates were δ= 0.584 (1.98), with 37 significantly positive and none significantly negative. Therefore, hypothesis 2 was verified. The hypothesis argument-supporting data established the empirical estimates derived from the results found via the average of individual regression, a2 (a2 = 0.382 (1.78)), with the average significantly positive. Thus, a greater market technical analysis weight is more likely caused by the generation of market anomalies.

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + a_2 h_{t-1} + \delta w_{t-1}^C$$
$$h_t = a_0 + a_1 h_{t-1} + a_2 h_{t-1} w_{t-1}^C + \delta w_{t-1}^C$$

Whether chartist weights change in terms of the weight of the different types of investments has a significant impact on whether there is a market bubble, and the collapse phenomenon is an interesting and worthy of study. These findings help clarify the key factors behind the market bubble and the collapse as reported in the literature. Using only basic pattern discrimination of chartist weights changes and the relationship between the market crash, this study uses the following equations to verify this issue, which, in turn, indicates that hypothesis 4 is supported.

$$P_{t+1}\big|_{before\ crisis} = \alpha_1 (P_t - F_t)\, w_t\big|_{before\ crisis} + \beta_1 (P_t - P_{t-1})(1 - w_t\big|_{before\ crisis}) + \varepsilon_t$$
$$P_{t+1}\big|_{after\ \ crisis} = \alpha_2 (P_t - F_t)\, w_t\big|_{after\ crisis} + \beta_2 (P_t - P_{t-1})(1 - w_t\big|_{after\ crisis}) + \varepsilon_t$$

Table 5 shows the empirical results for financial meltdown events, including the differences between pre- and post-weights of fundamentalists and chartists. Data from the financial turmoil in 2008 (May 2008), before and after one month and three months was examined. The data verifies the chartist average weight was significantly reduced during the financial turmoil. Furthermore, the 2000 Internet bubble can be used as an additional verification. Indeed, the results are the same after a technical analysis of the financial meltdown events, there is significant reduction in the weight average. These findings thus support hypothesis 3, in that chartist weight changes may lead to a market

Table 5. The variations of chartists' weights before and after crisis.

Crisis	Before One month	After One month	Difference	Before Three months	After Three months	Difference
2008 financial crisis	0.535	0.445	1.56**	0.521	0.47	1.01*
2000 Dotcom bubble	0.512	0.476	1.23**	0.508	0.481	0.83*

bubble phenomenon. Fundamentalist strategies may lead to a market crash because of investment related to HAM estimated relative value, as when there are higher chartist weights, the fundamentalist weights will be reduced.

5. Conclusions

This study attempts to answer several related questions. First, is the heterogeneous agent model originally proposed by Brock and Hommes (1998), compared with the rational representative agent model, able to explore the complex and nonlinear system of stock price? Can we distinguish fundamentalist and chartist agents, even characterizing the patterns of their time-varying weights? Moreover, do we observe a threshold value when considering the HAMs together with the threshold technique? Second, can we apply these time-varying chartist weights estimated from HAMs to explore a number of the stylized facts, volatility clustering and excess volatility? Finally, are the chartist weights related to financial bubbles? That is, is it that greater chartist weights are associated with a higher probability of bubbles occurring? Previous related HAM studies have focused on the theoretical perspective or simulation to explain financial stylized facts, but there is a dearth of empirical investigations on this subject (Chiarella et al., 2010; He and Li 2008; Huang et al., 2010). Although De Jong et al. (2009) and Ter Ellen and Zwinkels (2010) have empirically estimated HAMs to model asset prices, they have not explored the application of the dynamic agent weights, particularly chartist weights, to financial issues.

To address these questions, this paper adopted the international perspective using a 1996–2011 sample and empirically verified the validity of the HAMs for asset prices is supportive, as well as characterizing the time variance of chartist weights. Moreover, we determined that the predictive power of HAMs is better than traditional econometric models. Based on Threshold HAM, agents may adopt different trading strategies in terms of different return volatility. Furthermore, the stylized facts, such as volatility clustering and excess volatility, are positively related to chartist weights. Finally, financial bubbles are positively associated with chartist weights. In this paper, we extend earlier studies that emphasize the theory or simulation of HAMs and provide useful applications of chartist weights as a financial variable to explore financial phenomena, as well as provide an interesting behavioral research issue for future studies.

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