Overreaction Hypothesis or Volatility Spillover Hypothesis?

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Although price limits have been employed in many financial markets around the world, in the literature, the effectiveness of such price limits still gives rise to considerable debate. The main purpose behind the imposition of price limits is to reduce volatility; its rationale is referred to as the overreaction hypothesis. However, opponents of price limits have argued that price limits may have negative effects on financial markets so that volatility will spill over to the following days when asset prices reach the limits, i.e. volatility spillover hypothesis. Based on an agent-based framework in which traders are characterized by bounded rationality and are equipped with a genetic programming learning algorithm, the aim of this paper is to examine which hypothesis is supported in our simulated markets.

Keywords: Price Limits, Artificial Stock Market, Agent-Based Modeling, Genetic Programming.

1. Introduction

The financial market crashes that took place in 1987 gave rise to much debate regarding the markets from experiencing such large fluctuations. Recommendations that circuit breakers such as price limits and trading halts be implemented were some of the outcomes. The rationale for supporting price limits is referred to as the overreaction hypothesis in which the purpose of price limits is to reduce price volatility by repressing irrational behavior such as excessive speculation and mob psychology. People who support this argument claim that irrational traders tend to overreact to new information. In this situation, asset prices may encounter large changes so that they deviate from their fundamental values. The imposition of price limits then provides a cooling-off period for traders to reassess the intrinsic asset value. Volatility is then reduced. One of the most famous papers favoring the this proposition is that of Ma et al. (1989). By contrast, opponents of price limits argue that traders in financial markets are able to process information efficiently. Therefore, the imposition of price limits would generate negative effects, such as the phenomenon of volatility spillover. The volatility spillover hypothesis states that volatility increases in the subsequently trading days after the limit moves. Kim and Rhee (1997) provided a indepth investigation regarding the effects of price limits on the Tokyo Stock Exchange. Their findings supported the volatility spillover hypothesis.

Basically, the debates mainly result from the different assumptions regarding rationality that the researchers adopt to characterize market traders. However, in reality, traders are neither always irrational nor completely rational; instead, they are characterized by bounded rationality and rely heavily on the adaptive learning method to figure out how to manage their portfolio under uncertainty. In addition, financial markets are composed of many heterogeneous traders. They may possess heterogeneous beliefs, endowments, learning abilities, or attitudes toward risk aversion. It is quite difficult to derive analytical results for the effectiveness of price limits based on the interaction between many heterogeneous traders. Therefore, the simulation based on an agent-based framework seems to be an appropriate approach for overcoming these problems. To the best of our knowledge, Westerhoff (2003) proposing a chartist-fundamentalist simulation framework is the first to examine the issue regarding the effectiveness of price limits based on the agent-based modeling approach. Under a well-controlled environment without exogenous financial factors that may affect price dynamics, Westerhoff (2003) found that price limits can reduce volatility and make prices less distorted. These positive effects are more significant if more traders engage in trend-extrapolating behavior.

The remarkable work of Westerhoff does provide a novel track to reexamine the effects of price limits. However, several of his framework designs seem to have been little criticized. First, traders (fundamentalists) are assumed to know the fundamental values of the asset. Such an assumption is necessarily in Westerhoff's models, while it is not realistic. Second, although traders can switch between being chartists and fundamentalists, the forms of the technical or fundamental rules are pre-specified and do not change over time. The advantages of agent-based modeling are that it not only provides a framework for the interaction between many heterogeneous agents but also explores emerging phenomena from the bottom-up. This last aspect crucially relies on how the agents' behavior is represented and how it evolves. The representations should incorporate the ways of decision making which consist of the behavior of learning and adaptation. Pre-determining the range and type of forecasting rules may limit the traders' ability to process information and possibly result in biased outcomes. Besides, in the absence of the evolution of the trading strategies, the heterogeneity of the traders' beliefs, the momentum for the profound financial phenomena, is then restrained.

In this paper, we propose a simulated artificial stock market in which traders are characterized by bounded rationality and are equipped with a genetic programming (GP) learning algorithm to examine which hypothesis is supported. Since GP is able to represent hierarchical strategies of different sizes and shapes as time goes on, it is then employed to form and evolve traders' expectations. The advantage of this modeling is that traders are freely allowed to form various types of forecasting functions which may be fundamental-like or technical-like rules in different time periods. Therefore, compared with previous studies, our framework may reveal more interesting and valuable features.

2. Market Structure and Learning of Traders

Following the same framework of Yeh (2008), we consider the standard asset pricing model which is employed in Grossman and Stiglitz (1980). In this market, there are two assets for traders to invest in. One is the risk free asset, money, which pays a constant interest rate r, and the other is the risky asset, stock, with a stochastic dividend process (D_t) not known to traders. Assume that traders have the same constant absolute risk aversion (CARA) utility function, i.e., $U(W_{i,t}) = -exp(-\lambda W_{i,t})$, where $W_{i,t}$ is the wealth of trader i in period t, and λ is the degree of absolute risk aversion.

By myopically maximizing the one-period expected utility function, trader i's optimal demands for the stock, $h^*_{i,t}$, is as follows:

$$h^*_{i,t} = \frac{E_{i,t}(P_{t+1} + D_{t+1}) - (1+r)P_t}{\lambda \sigma^2_{i,t}}, \tag{1}$$

where $\sigma^2_{i,t}$ is the conditional variance of $(P + D)$ given the information up to t, $I_{i,t}$. In addition, if it is supposed that the current stock holding for trader i is at the optimal level, i.e., $h^*_{i,t} = h_{i,t}$, then the trader's reservation price, P_i^R, can be derived.

$$P_i^R = \frac{E_{i,t}(P_{t+1} + D_{t+1}) - \lambda \sigma_{i,t}^2 h_{i,t}}{1+r}. \tag{2}$$

Following the same architecture used in Yeh (2008), the formation of expectations is represented by GP, and we assume the following functional form for $E_{i,t}(.)$:

$$E_{i,t}(P_{t+1}+D_{t+1}) = \begin{cases} (P_t + D_t)(1 + 0.001 f_{i,t}\theta_0), & \text{if } \; -1000.0 \leq f_{i,t} \leq 1000.0, \\ (P_t + D_t)(1+\theta_0), & \text{if } \; f_{i,t} > 1000.0, \\ (P_t + D_t)(1-\theta_0), & \text{if } \; f_{i,t} < -1000.0. \end{cases} \tag{3}$$

where $f_{i,t}$ is generated by GP. At the end of each period, each trader updates his estimated conditional variance which is described as follows:

$$\sigma_{i,t}^2 = (1-\theta_1)\sigma_{i,t-1}^2 + \theta_1[(P_t + D_t) - E_{i,t-1}(P_t + D_t)]^2. \tag{4}$$

Each trader is endowed with N_I forecasting models represented by GP. The performance of each forecasting model is indicated by the value of strength which is defined by

$$s_{i,j,t} = -\sigma_{i,j,t}^2, \tag{5}$$

where strength$_{i,j,t}$ is the strength of the jth model for trader i in period t. At the beginning of each period t, each trader randomly chooses N_T out of N_I models. The one with the highest strength value is selected as the model he uses in this period. At the end of each period, the model with the lowest strength is replaced by the model which is created by means of crossover, mutation, or immigration.

A simplified DA is employed as the trading mechanism. Each period is decomposed into N_R rounds. At the beginning of each round, a new random permutation of all traders is performed to determine their order of bid and ask. If a bid (ask) exists, any subsequent bid (ask) must be higher (lower) than the current one. For the sake of simplicity, only a fixed amount of stock (Δh) is traded in each transaction. The last transaction price (closing price) in each period is recorded as the market price for this period.

3. Results

In our simulations, initially, each trader is endowed with one share of stock and \$100 dollars in cash. A maximum stock holding of 20 shares is imposed on the traders. In addition, they are not allowed to sell short or buy on margin. The information regarding the stock price and dividend history up to the last 5 periods is made available so that traders can use it to form their expectations. In each simulation, it takes 10,000 periods and each period consists of 50 rounds.

Four markets with different price limits together with a market without the price limit rules are considered. From Market A to Market D, the maximum allowed percentage in terms of the price change in each period is set to be 5%, 10%, 20%, and 30%, respectively, while there exist no price limits in Market E. We perform twenty runs for each market, and each run starts with a different random seed.

Following the procedure employed in Kim and Rhee (1997), we perform an event study to examine the existence of volatility spillover. The event, $\mathrm{Day}_{\mathrm{Hit}}$, is defined as the locked limit days on which the daily closing prices reach the price limits. Similarly, $\mathrm{Day}_{0.9}$ ($\mathrm{Day}_{0.8}$) represents the event in which the daily closing prices reach at least 90% (80%) of the limits but less than 100% (90%) of the limits. Consider an 11-day event window: Day -5 to +5. Day 0 indicates the event day, Day -i and Day +i (i=1, 2,..., 5) are the ith day before and after the event day, respectively.

The volatility is measured by the absolute return. The existence of volatility spillover could be supported by the phenomenon that the volatility during the post-event periods (Day 1 to Day 5) for the event $\mathrm{Day}_{\mathrm{Hit}}$ would be higher than those for $\mathrm{Day}_{0.9}$ and $\mathrm{Day}_{0.8}$. The average absolute returns over the 11-day window across twenty runs for all events are reported in Table 1. The values shown in the parentheses are the corresponding results observed in Market E when the respective price limits are set as the limit criteria.

It is shown that the volatility on Day 1 is rather small compared with that on Day 0 under $\mathrm{Day}_{\mathrm{Hit}}$. This phenomenon is usually employed as the evidence in support of the effectiveness of price limits in reducing volatility. However, volatility tends to decline after the day characterized by large volatility. Such a phenomenon is also observed in the events $\mathrm{Day}_{0.9}$ and $\mathrm{Day}_{0.9}$, and the corresponding results in Market E. Therefore, the conclusion that is purely based on this result is too premature.

When focusing on the volatility during the post-event periods for $\mathrm{Day}_{\mathrm{Hit}}$ in comparison with that for $\mathrm{Day}_{0.9}$, we found several interesting pictures. First, from Market A to Market D, most of the post-event periods, especially from Day 1 to Day 3, exhibit lower volatility for $\mathrm{Day}_{\mathrm{Hit}}$ than those for $\mathrm{Day}_{0.9}$ and $\mathrm{Day}_{0.8}$.[a] This result is contrary to the volatility spillover

[a]These few exceptions disappear when the volatility is measured based on the sample in

hypothesis and reveals the effectiveness of price limits in reducing volatility. Second, the usefulness of price limits can be further confirmed by the corresponding results in Market E. Because there are no price limits imposed on Market E, it is to be expected that no significant difference in the magnitude of volatility between $\mathrm{Day}_{\mathrm{Hit}}$ and $\mathrm{Day}_{0.9}$ (or $\mathrm{Day}_{0.8}$) during the post-event periods would be observed if traders were able to process information efficiently, while we observe the opposite result. In Market E, it is shown that $\mathrm{Day}_{\mathrm{Hit}}$ possesses higher volatility than $\mathrm{Day}_{0.9}$ and $\mathrm{Day}_{0.8}$ during the post-event periods. This indicates an important phenomenon: under no price limits, the traders' overreaction persists for several periods so as to generate large volatility in the subsequent periods.

4. Conclusion

In this paper, we propose an agent-based framework in which traders are endowed with a GP learning algorithm to examine the effects of price limits. Our results support the view that the imposition of price limits helps to reduce volatility. Such a positive effect results from the function of the price limits by which traders' overreaction behavior is curbed. This function can be evidenced by the results from the benchmark market where no price limits are imposed.

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which the consecutive locked limited days except for the first day are excluded.

Table 1. Volatility spillover test.

			Market A				
Day	Day_{Hit}			$\text{Day}_{0.9}$			$\text{Day}_{0.8}$
-5	0.023666 (0.149832)	$>$	$(>)$	0.022937 (0.073207)		$(>)$	0.023258 (0.070109)
-4	0.023764 (0.149196)			0.023676 (0.074670)			0.023439 (0.072023)
-3	0.023543 (0.150632)			0.023424 (0.075940)		$(\gg)$	0.023106 (0.071123)
-2	0.023345 (0.151049)		$(\ll^{\dagger})$	0.023597 (0.080029)		$(\gg)$	0.023709 (0.074347)
-1	0.023193 (0.154048)		$(\ll^{\dagger})$	0.023413 (0.078127)		$(\gg)$	0.023965 (0.076299)
0	0.047849 (0.292818)	$\gg$	$(\gg)$	0.043240 (0.043826)	$\gg$	$(\gg)$	0.038654 (0.039281)
1	0.022997 (0.156543)	$\ll$		0.024125 (0.076044)		$(\gg)$	0.024434 (0.073130)
2	0.023210 (0.150610)		$(\gg)$	0.023694 (0.074771)			0.024152 (0.074685)
3	0.023404 (0.144016)	$<$	$(\gg)$	0.024160 (0.075900)		$(\gg)$	0.023816 (0.072890)
4	0.023595 (0.141907)		$(\gg)$	0.023861 (0.076858)			0.023829 (0.078823)
5	0.023596 (0.137581)		$(\gg)$	0.023164 (0.077697)			0.023785 (0.082631)
			Market B				
Day	Day_{Hit}			$\text{Day}_{0.9}$			$\text{Day}_{0.8}$
-5	0.032752 (0.168719)		$(\ll^{\dagger})$	0.035436 (0.153249)			0.033239 (0.138730)
-4	0.032838 (0.169368)		$(<^{\dagger})$	0.032835 (0.126844)			0.033577 (0.134040)
-3	0.031463 (0.172423)	$\ll$	$(\ll^{\dagger})$	0.036270 (0.127013)	$\ll$		0.034661 (0.117958)
-2	0.031137 (0.172359)			0.034249 (0.110415)			0.030881 (0.103513)
-1	0.030611 (0.174855)		$(\ll^{\dagger})$	0.031082 (0.103277)			0.032082 (0.099322)
0	0.098008 (0.402926)	$\gg$	$(\gg)$	0.090859 (0.087830)	$\gg$	$(\gg)$	0.081115 (0.078520)
1	0.030120 (0.179710)			0.033088 (0.098574)			0.034607 (0.093242)
2	0.030969 (0.171351)			0.029291 (0.118480)			0.033229 (0.109439)
3	0.031548 (0.161966)		$(>)$	0.033945 (0.106521)			0.032970 (0.113678)
4	0.032943 (0.157823)		$(>)$	0.035222 (0.110303)			0.034723 (0.113538)
5	0.032963 (0.151091)		$(>)$	0.030858 (0.118352)			0.028434 (0.123793)
			Market C				
Day	Day_{Hit}			$\text{Day}_{0.9}$			$\text{Day}_{0.8}$
-5	0.056924 (0.163372)		$(<)$	0.060898 (0.185487)			0.059923 (0.175879)
-4	0.055122 (0.168000)		$(\ll)$	0.054057 (0.180198)			0.055278 (0.185663)
-3	0.052814 (0.178986)			0.057339 (0.156038)			0.053322 (0.173424)
-2	0.051905 (0.183861)			0.055320 (0.149219)			0.055662 (0.139002)
-1	0.050731 (0.193453)		$(<^{\dagger})$	0.060949 (0.129167)			0.063684 (0.119239)
0	0.198250 (0.510969)	$\gg$	$(\gg)$	0.186126 (0.181762)	$\gg$	$(\gg)$	0.165283 (0.162109)
1	0.052509 (0.192856)		$(<^{\dagger})$	0.050989 (0.111918)			0.058799 (0.107527)
2	0.053544 (0.179468)			0.048747 (0.123055)	$<$		0.062056 (0.119552)
3	0.053801 (0.167745)			0.052664 (0.124877)	$\ll$		0.067410 (0.123606)
4	0.055726 (0.162370)			0.057726 (0.130077)			0.056294 (0.123431)
5	0.057759 (0.157704)			0.051263 (0.134017)			0.051583 (0.124296)
			Market D				
Day	Day_{Hit}			$\text{Day}_{0.9}$			$\text{Day}_{0.8}$
-5	0.088427 (0.163195)	$>$		0.083744 (0.140782)			0.092841 (0.155321)
-4	0.085684 (0.169355)			0.084553 (0.153294)	$<$		0.097135 (0.132901)
-3	0.083288 (0.181965)	$>$		0.080364 (0.145145)			0.087669 (0.152740)
-2	0.082783 (0.197250)	$>$		0.079961 (0.139986)	$\ll$		0.109682 (0.142898)
-1	0.082791 (0.219247)			0.082645 (0.108570)	$\ll$		0.108204 (0.122335)
0	0.297524 (0.613896)	$\gg$	$(\gg)$	0.294005 (0.276500)	$\gg$	$(\gg)$	0.249623 (0.247481)
1	0.087245 (0.219250)	$>$		0.082347 (0.093928)	$\ll$		0.106882 (0.097889)
2	0.085981 (0.199076)			0.087489 (0.108124)			0.097025 (0.107300)
3	0.085319 (0.183008)			0.087557 (0.114225)	$<$		0.095127 (0.111590)
4	0.087743 (0.174737)	$>$	$(>)$	0.085153 (0.117507)			0.081516 (0.113386)
5	0.089365 (0.166962)			0.088167 (0.122926)			0.092818 (0.124391)

Note: $>$ and $\gg$ (or $<$ and $\ll$) mean that, based on the Mann-Whitney test, the medians on the left are significantly greater (smaller) than those on the right at the 5% and 1% significance levels, respectively. However, the values shown in the table are the means rather than the medians. Therefore, we observe the inconsistent directions by comparing the means and medians. Such an inconsistency is indicated by the symbol †. Because most of the inconsistency occurs in the pre-event periods, our general conclusion is unaffected if the means are replaced by the medians.