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THE WORKING OF CIRCUIT BREAKERS WITHIN PERCOLATION MODELS FOR FINANCIAL MARKETS

GUDRUN EHRENSTEIN
Institute for Theoretical Physics, Cologne University
Zülpicherstraße 77, D-50937 Köln, Germany
ge@thp.uni-koeln.de

FRANK WESTERHOFF
Department of Economics, University of Osnabrück
Rolandstraße 8, D-49069 Osnabrück, Germany
frank.westerhoff@uos.de

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We use a modified Cont–Bouchaud model to explore the effectiveness of trading breaks. The modifications include that the trading activity of the market participants depends positively on historical volatility and that the orders of the agents are conditioned on the observed mispricing. Trading breaks, also called circuit breakers, interrupt the trading process when prices are about to exceed a pre-specified limit. We find that trading breaks are a useful instrument to stabilize financial markets. In particular, trading breaks may reduce price volatility and deviations from fundamentals.

Keywords: Econophysics; percolation models; financial markets; trading breaks.

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1. Introduction

After the stock market crash of October 1987, many stock markets have imposed circuit breakers in order to curb speculative activity (for comprehensive surveys see, e.g., France *et al.*,[1] Harris,[2] Kim and Yang[3]). Such regulatory mechanisms halt the trading process for a given period of time when the market price reaches a pre-specified level. During that time period — regulators often argue — nervous market participants have the opportunity to cool off and to reevaluate the state of the market. Afterwards, trading resumes as usual.

While policy makers seem to be optimistic with respect to the working of trading breaks, many economists are pessimistic. In efficient markets, for instance, asset prices are said to reflect all available information, and prices change only in response to relevant new information. Fama[4] therefore argues that high volatility per se is not necessarily a bad thing for the economy, as long as the volatility comes from a rational response to changes in fundamental values. Fama warns that trading breaks may lead to a delayed price discovery process and to volatility spillover since necessary immediate price corrections are transferred to subsequent days.

However, the efficient market hypothesis has recently been challenged by new behavioral finance theories. In particular, models with heterogeneous interacting agents seem to catch some key characteristics of financial markets quite well. For instance, Kirman,[5] Palmer *et al.*,[6] Brock and Hommes,[7] Lux and Marchesi[8] or Farmer and Joshi[9] develop models in which the price dynamics is influenced through the activity of boundedly rational speculators (and does not solely depend on exogenous news). Complicated endogenous dynamics may arise due to nonlinear trading strategies, switching between trading strategies and markets, or social interactions such as herding behavior. One reason why these models may be regarded as quite powerful is that they have the potential to generate bubbles and crashes, excess volatility, fat tails for the distributions of returns, uncorrelated returns and volatility clustering. These features are also observed in real financial markets (Mantegna and Stanley,[10] Lux and Ausloos[11]).

The goal of this paper is to use a modified Cont–Bouchaud model to further explore the effectiveness of trading breaks. Cont and Bouchaud[12] develop a model that explicitly takes into account interactions between market participants through imitation and/or communication. Their model is able to generate uncorrelated returns and fat tails for the distribution of returns. The Cont–Bouchaud approach has been extended in various ways (see, e.g., Stauffer[13]). Here we follow two interesting suggestions. First, we incorporate a fundamental value and thus agents may condition their buying and selling decision on the observed mispricing in the market (as in Chang and Stauffer[14]). Second, the activity of the traders is correlated with past price volatility (as in Stauffer and Jan[15]), meaning that when price volatility increases (decreases) more (less) traders are active (inactive). As a result, the modified Cont–Bouchaud model has furthermore the potential to produce bubbles and crashes, excess volatility and volatility clustering, thus mimicking some important stylized facts of financial markets. What happens if regulators impose trading breaks in such an environment? Our Monte-Carlo study reveals that trading breaks have the power to reduce both volatility and mispricing. Only when the maximum allowed price change is set very low, prices may lose their ability to track fundamental values.

As pointed out in the survey of Kim and Yang,[3] pure empirical results conflict about the success of trading breaks and the validity of some of the methodologies used in the past is questionable. One obvious problem of empirical studies is that circuit breakers are rarely triggered in reality (price changes of 5% occur, but not very often) and thus it is difficult to obtain sufficient evidence to evaluate their effectiveness. Simulations studies — such as ours — allow us to generate as many observations as needed. In addition, one may control all kinds of shocks and measure variables precisely. This avenue of research has also been followed by Westerhoff.[16,17] Using low-dimensional nonlinear models with interacting technical and fundamental traders, he finds that trading breaks may stabilize financial markets. To be on the safe side, however, different behavioral finance models should be applied. The usefulness of the Cont–Bouchaud model with respect to policy analysis has recently been demonstrated by Ehrenstein[18] and Ehrenstein *et al.*[19] where it is shown that the imposition of transaction (Tobin) taxes has most likely a stabilizing impact on financial market dynamics.

The reminder is organized as follows. In Sec. 2, we sketch the main building blocks of our model. In Sec. 3, we present and discuss our results. The last section concludes and points out some extensions for future work.

2. A Modified Cont–Bouchaud Model

Following Stauffer,[13] we put the Cont–Bouchaud model on a $L * L$ square lattice. In our case, we set $L = 31$. Each site of the lattice is occupied randomly, with probability p, by a trader, and left empty with probability $(1 - p)$. Traders which are nearest neighbors form clusters (as usual in percolation theory), and for p close to some percolation threshold $p_c = 0.5927$, an infinite cluster exists besides many finite clusters (the largest cluster is, however, ignored). Each remaining cluster acts together in trading, that means that all traders within a cluster simultaneously either buy (with probability a), sell (also with probability a), or are inactive (with probability $(1 - 2 * a)$. The traded amount is proportional to the cluster size. The log of the price is adjusted with respect to the excess demand. If buying exceeds selling, the price goes up and if selling exceeds buying, the price goes down. Since log price changes of the Cont–Bouchaud model may be large integers, we have to normalize the returns. This is done with the help of the parameter *maxwin*. Suppose that $maxwin = 0.2$, then the return that would occur when all clusters are active and trade in the same direction is set to 0.2 (such a situation only rarely occurs).

The first modification is to include a fundamental value which is assumed to follow a random walk. As in Chang and Stauffer,[14] the probabilities to buy and to sell are no longer equal but depend on the mispricing in the market: If the log of the price P is above its log fundamental value F (the market is overvalued), then the probability to sell is higher than the probability to buy. To be precise, the probability to sell is no longer a but $(1 + \varepsilon * (P - F)) * a$, and the probability to buy is $(1 - \varepsilon * (P - F)) * a$. The parameter ε is positive and the buy and sell probabilities are restricted between 0 and 1. Within our model, prices may thus deviate from fundamentals, but this mechanisms also implies a mean reversion pressure: Overvaluation creates excess selling and undervaluation creates excess buying.

With the second modification, we relate the activity level of the traders to past changes in price volatility (similar to Stauffer and Jan[15]). This means that in calm periods the traders become lazy whereas in turbulent periods they act more hectic. This is implemented as follows: When price volatility increases, the activity level a increases and when price volatility decreases, the activity level a decreases. The evolution of a is limited within [0.02, 0.5]. Note that the total number of traders remains constant. Trading breaks are implemented as follows: After the orders of the traders have been collected, we first compute a new hypothetical price. If we observe that this price violates the imposed price limit, it will be reset to the limit. Suppose, for instance, that regulators have imposed a price limit of 3% and that the current price is 100. If the new hypothetical price is computed as 105, it will be reset to 103. Obviously, this affects the volatility (which is in this time step 3%) and thus also the activity level of the traders (since their impact depends on past observed volatility). The next section discusses how such trading breaks may affect the price dynamics.

3. Some Monte Carlo Results

Figure 1 shows how volatility (defined as average absolute return) and distortion (defined as average absolute distance between log prices and log fundamental values) react to an increase in the maximal allowed price change. These so-called price limits are varied between 0 and 3% in small discrete steps. Each time, volatility and distortion are computed from a very large number of observations. The results are presented for 9 different parameter combinations (from bottom to top: (1) $\varepsilon = 0.05$, $maxwin = 0.1$, (2) $\varepsilon = 0.075$, $maxwin = 0.15$, (3) $\varepsilon = 0.1$, $maxwin = 0.2$, (4) $\varepsilon = 0.125$, $maxwin = 0.25$, (5) $\varepsilon = 0.15$, $maxwin = 0.3$, (6) $\varepsilon = 0.175$, $maxwin = 0.35$, (7) $\varepsilon = 0.2$, $maxwin = 0.4$, (8) $\varepsilon = 0.225$, $maxwin = 0.45$ and (9) $\varepsilon = 0.25$, $maxwin = 0.5$). As can be seen, the sharper the price limit becomes, the lower is the volatility. The relation between price limits and distortion is nontrivial. First the distortion decreases, but after reaching a minimum value it starts to increase again. Taking our estimates literally, we see that trading breaks may considerably decrease price fluctuations and deviations from fundamental values.

What is going on in our artificial financial market? Note first that trading breaks always have a direct effect on the price dynamics. If, for instance, the maximal allowed price change is 2%, then there will be no price change larger than 2%. But within our model, trading breaks also have an important indirect effect. Since the activity of the traders positively depends on the evolution of past price volatility, they will become less active/hectic when extreme price changes are excluded. A lower activity level furthermore decreases volatility and most likely distortions. However, trading breaks should be used with caution. When the maximal allowed price change is too restrictive, prices do not track their fundamental values any more. Hence, financial markets need some price flexibility, but maybe not full price flexibility. What is remarkable is that the results presented here are quite close to the results presented in Westerhoff,[16,17] despite the fact that two distinct modeling approaches are used. This may give rise to be optimistic about the effectiveness of trading breaks.

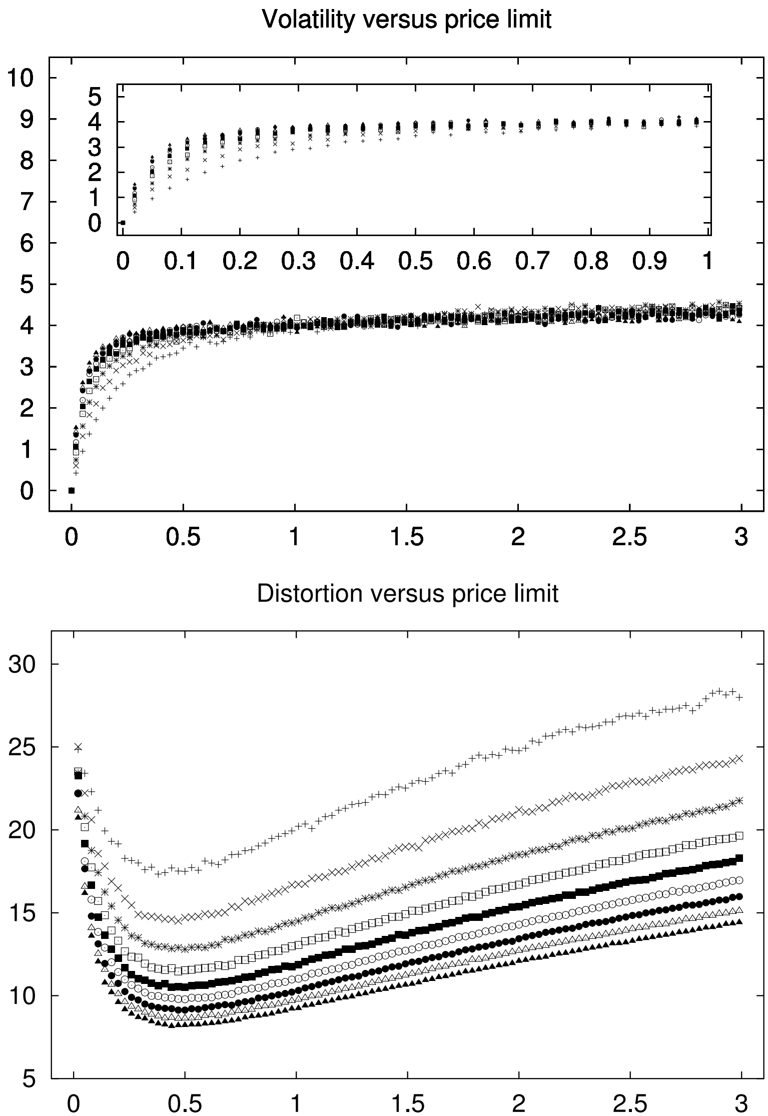

Fig. 1. The impact of trading breaks on volatility (top) and distortion (bottom) for different parameter settings. Volatility is multiplied with 10^{-5} and distortion with 10^{-2}.

4. Conclusions

Many regulators of financial markets hope that trading halts reduce price volatility by giving traders an opportunity to cool of and think before they act, though there is no proof that a mandatory trading halt makes stampeding traders in fact calm down. To the contrary, advocates of the efficient market hypothesis argue that trading breaks only lead to a delayed price discovery and to volatility spillover. We use a modified Cont–Bouchaud model to explore this issue and find that trading breaks may have the potential to stabilize financial markets. Only when the price variability is extremely restricted, prices stop following their fundamentals and mispricing increases.

Let us finally point out two avenues for future research. First, it would be interesting to investigate different order matching mechanisms. In our approach, trading is interrupted when prices reach their limit and all left orders are not executed (i.e., they are canceled). Within a limit order book mechanism, some of the orders may survive for some time and have an impact on the future price dynamics. Second, traders may react strategically to price limits. For liquidity reasons, traders may submit orders in advance when prices are close to the limit. This may then push prices indeed to the limit.

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