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OFFSETTING THE DISPOSITION EFFECT WITH A STOP-LOSS RULE

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Abstract. We put forward an agent-based model of the stock market, where the behavior of agents showing the disposition effect can be offset by that of others using a stop-loss rule. In a stop-loss order, a stock is sold automatically if it drops below a threshold value. The disposition effect is the tendency to sell stocks that have gained in value ("winners") and keep the ones that have fallen in value ("losers"). After showing the model can replicate actual return behavior considering data from the recent mini flash crashes, we explore the consequences of altering key behavioral parameters. Our primary result is that the presence of stop-loss agents in a non-Gaussian environment can offset the disposition effect. Furthermore, we find differing return targets to contribute to market efficiency, and a negative shock to a market sentiment index to cause the stock price to dip and trade volume to grow. Finally, increasing overconfidence generates higher trade volume.

Keywords: agent-based model; stock market; disposition effect; stop-loss rule.

2010 AMS Subject Classification: 91B26.

1. Introduction

Agent-based models can replicate the extreme moves observed in actual stock markets. Coupled with heterogeneous beliefs [1], such models also can take into account psychological features, such as market sentiment and overconfidence [2, 3]. Here we suggest the "disposition effect" (the tendency to sell winners and keep losers) can be offset by an automated stop-loss rule, which is a predetermined policy that reduces the portfolio's exposure after it reaches a certain threshold of cumulative losses.

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The most accepted explanation for the disposition effect is prospect theory. Because investors dislike incurring losses much more than they enjoy making gains, and investors are willing to gamble in the domain of losses, they will hold onto stocks that have lost value (relative to the reference point of their purchase) and will be eager to sell stocks that have risen in value. The disposition effect should lead to market failure in that it distorts the role of prices in conveying information. Indeed, disposition-effect investors will hold onto a stock even if they think it will fall further in value. The very existence of stop-loss investors can prevent such a massive market failure in that they can offset disposition-effect investors. Although this may seem obvious, our contribution is to show how the mechanics of the offsetting behavior operate with the help of a model.

Indirect evidence supports the fact that in real-world markets, stop-loss rules can compensate for the disposition effect. Although stop-loss rules are ineffective in efficient markets [4], Kaminski and Lo [4] find stop-loss rules can reduce losses in a non-Gaussian environment, although they do not consider the presence of the disposition effect. Their result matches the one we find in this work – the presence of stop-loss agents can offset the disposition effect given that the environment is non-Gaussian.

The next section presents the model; the results are shown in the subsequent section; and the last section concludes the study.

2. Model

We consider a market populated by $n = 10,000$ agents divided into two groups: disposition-effect investors (Eqs. (1)−(4) below) and stop-loss investors (Eq. (9)). We assign exogenously the group to which each agent pertains, as well as group size. The disposition-effect investors are modeled using the value function of cumulative prospect theory [5]. The investors under the stop-loss rule are modeled building on Ref. [4]. Each agent collects information from his neighborhood, and there are two exogenous parameters: 1) the ecology of distinct expected returns (x_i), and 2) how one agent values the information he currently holds compared to information received from neighbors (ω_i). They also consider information from a measure of sentiment at the market level. We also assume investors buy more stocks only after they have closed their previous position.

Each time period *t*, agent *i* must decide between either buying or selling the stock, or doing nothing. He enters the market with probability ψ_{it}, where:

$$\psi_{it} = \begin{cases} \nu_{it} & \text{if he owns stocks} \\ \gamma_{it} & \text{if he has no stocks} \end{cases} \tag{1}$$

If investor i owns stocks, he is prone to the disposition effect, which is modeled by a version of the value function of cumulative prospect theory:

$$\nu_{it} = \begin{cases} x_i^{\alpha}, \text{ if } x_i \geq 0 \text{ (gains)} \\ -\lambda\left(-x_i\right)^{\alpha}, \text{ if } x_i < 0 \text{ (losses)} \end{cases} \tag{2}$$

Here, we interpret the values of x_i as representing the fact that each agent i has a distinct expected return. The investor places an order if a cumulative return X_i overshoots his expected return x_i. (If x_i is large enough the investor may adopt a buy-and-hold strategy.) Parameter $\alpha \in (0,1]$ governs the function concavity, and λ measures loss aversion. We set $\lambda = 2.25$ (as in Ref. [5]) and thus endorse the prospect theory explanation for the disposition effect as loss aversion: The response to losses is more than twice as strong as the response to corresponding gains. As argued by Barberis and Xiong [6], when investors gain utility from accumulated operations during a year or other given time period, prospect theory does not lead to the disposition effect. However, when utility accrues from simple buy and sell operations, as in our model, prospect theory does predict a disposition effect.

We define a market sentiment index I at the market level as:

$$I = \frac{b_t - s_t}{b_t + s_t + h_t} \tag{3}$$

where $I \in \left(-1,1\right)$, b is the number of buyers; s is the number of sellers; and h is the number of agents who are neither buying nor selling. The market sentiment is bearish ($I \to -1$) if the investor expects downward price movement due to the presence of many sellers. In the presence of many buyers, the market sentiment is bullish ($I \to 1$). A current value of the index I stays in place until the investor executes a future consultation of his neighborhood. Each agent uses index I differently, and the random parameter $\beta_i \in [0,1]$ captures this fact. In a full-fledged equilibrium model, a market clearing condition would imply that index (3) should be zero. In our disequilibrium model, however, we only expect (3) to asymptotically converge to zero when the parameter configuration and model dynamics will lead to stability.

Assuming a bidimensional Moore grid [7], the neighbors of influence were defined by a "nine-neighbor square." The lattice size was defined to have 100×100 cells, totaling 10,000 traders. Eight neighbors can provide any of three types of information for the agent at hand: buy, sell or hold on his position. Such information will be used in the subsequent period. If the agent himself initially possesses some piece of information, then $O_i = 1$; if not, $O_i = 0$. His own information comes from his last move. If the move was a purchase, his private information is a purchase. If the move was a sell, his private information is a sell. If in the last move the investor neither purchased nor sold, he doesn't have his own information, in which case $O_i = 0$. He puts a weight ω to the value of his own information as compared to that possessed by his neighbors, $\omega_i O_i$. If $\omega_i = 0$, the agent pays no attention to the information he owns. If $\omega_i = 1$, his own information is given the same weight as that of his neighbors. As ω_i grows, the weight given to his own information increases, and as $\omega_i \to \infty$, he considers only his own information, in which case we can say he exhibits "overconfidence."

If the investor has no stock, his probability γ_{it} is then:

$$\gamma_{it} = \begin{cases} \dfrac{\sum_{j=1}^{8} b_{jt} + \omega_i O_i}{\sum_{j=1}^{8} (b_{jt} + s_{jt} + h_{jt}) + \omega_i O_i} + \beta_i I, & if \leq 1 \\ 1 \end{cases} \tag{4}$$

The probability γ_{it} is greater the larger the market sentiment index is. In the first period γ_{it} refers solely to his probability to buy because he starts with no stocks. An equation reminiscent of Eq. (4) is suggested in Ref. [8]. The neighborhood is important for current decisions, but a wide-market index is more appropriate for evaluating market sentiment. Using a neighborhood measure would be too narrow. We assume investors can get information about the index, following Shiller [9]. Shiller uses questionnaires to get what we consider here as the "neighborhood perspective," and assumes agents know the market sentiment from a broader market perspective. Since index I is not computed for every time period, the neighborhood continues to be key for the current decisions of the agents in this model. Of note, in a given time period, the weight ascribed to the neighborhood is much greater than that of the index. (The probability to sell is analogous to Eq. (4).)

Individual choices are also constrained by what the group collectively does. When the parameter configuration and the model dynamics lead to stability and market clearing, such a constraint can be modeled by an excess demand function D_t:

$$D_t = \frac{b_t - s_t}{n} \tag{5}$$

The stock price p in the time period t is then computed using the previous price and the excess demand. We consider a hyperbolic tangent functional form for the excess demand (as is Ref. [10]):

$$p_t = p_{t-1}\left(1 + \tanh D_t\right) \tag{6}$$

The initial price is arbitrary and does not interfere with the model dynamics. The agent's initial realized return r_i is given by:

$$r_{it} = \ln p_t - \ln p_{t-1} \tag{7}$$

Each agent maintains the cumulative return X_i from the date of purchase of the stock, defined by:

$$X_i = \frac{p_t - q_i}{q_i} \tag{8}$$

where q_i is the purchasing price.

An agent relying on the automated stop-loss rule places the stop order ρ_t considering some loss threshold [8]:

$$\rho_t = \begin{cases} \text{Buy if} & r_i > \delta_i \\ \text{Hold if} & -x_i \le X_i \le \lambda x_i \\ \text{Sell if} & X_i < 0 \text{ and } X_i < -x_i \\ \text{Sell if} & X_i > 0 \text{ and } X_i > \lambda x_i \end{cases} \tag{9}$$

where δ_i is the threshold for the automated order to be triggered, which assumes a different value for each agent. The first line in Eq. (9) refers to current return when the investor owns no stocks. If the investor owns any stocks, the current return no longer has any influence for him. He will look at the cumulative return, that is, the purchase value minus the current value. He is now contemplating one of the remaining three lines in Eq. (9). For this reason, there will be no situation in which the investor looks at the current return and the cumulative return at the same time. The first line is a rule of entry, then the investor picks one of the three remaining lines. The second line refers to the period in which the investor is inactive; the third is the rule of exit if the cumulative returns are negative; and the fourth is the exit rule for the cases where the cumulative return is positive. Eq. (9) is borrowed from Ref. [4]. Unlike the environment of the disposition effect (Eqs. (1)−(4)), in Eq. (9), an agent sells faster in a low and waits longer in a high. The stop-loss investors are committed to a deterministic rule, but some find it difficult to adhere to such a rule and may behave stochastically, in which case they follow the value function of prospect theory.

3. Results

To check for the empirical relevance of our model, we considered data from the recent mini flash crashes occurring in some stocks listed on the Dow Jones Industrial Average (Table 1 and Fig. 1). Returns are clearly non-Gaussian. Fig. 2 shows the histogram of the Apple stock and its poor Gaussian fit.

Table 1. The stock returns for the period covering the mini flash crashes are not normally distributed.

Stock	*Time period*	*Lilliefors test*	*Excess kurtosis*	*Reject normality?*
Abott Labs	April, 29 2011 – May, 31 2011	0.001	15.36	Yes
Apple	March, 16 2012 − March, 30 2012	0.001	24.33	Yes
Cisco Systems	July, 20 2011 − July, 29 2011	0.001	24.31	Yes
Core Molding	August, 19 2011 − August, 31 2011	0.001	9.69	Yes

Note: The critical values were computed using Monte Carlo simulation for sample sizes less than 1,000 and significance levels between 0.001 and 0.5. The result 0.5 means the data are generated by a Gaussian, and 0.001 means rejection of Gaussianity

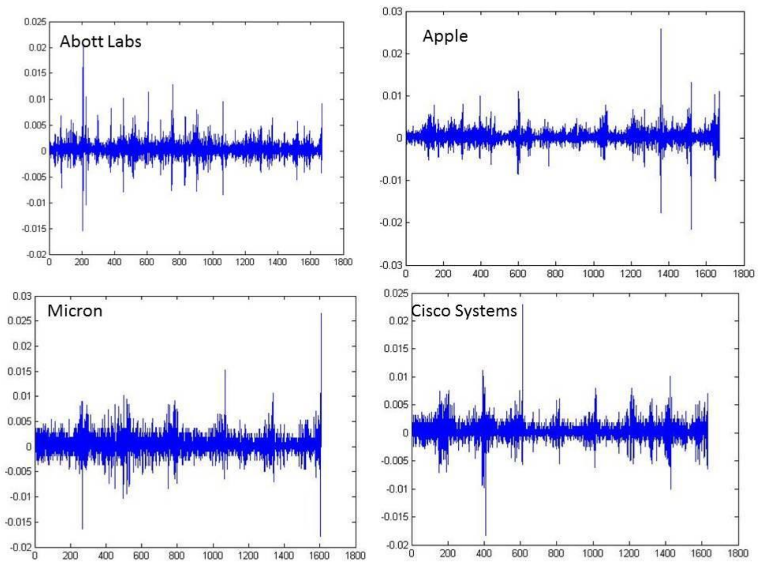

Fig. 1. Log-returns of the stocks for the period of the mini flash crashes

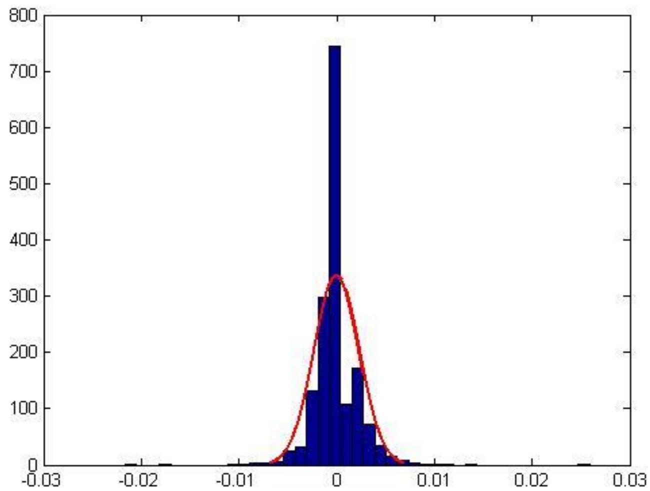

Fig. 2. Apple's return histogram and Gaussian fit

Fig. 3 shows the log-returns generated by our model for $\omega_i = 1$; an upper bound of $\bar{x} = 0.16$; four groups of expectation targets ($i = 4$); and 25 percent of stop-loss agents. Fig. 4 shows the histogram. After comparing with the previous Figs. 1 and 2, one can see that the model roughly replicates actual stock market behavior.

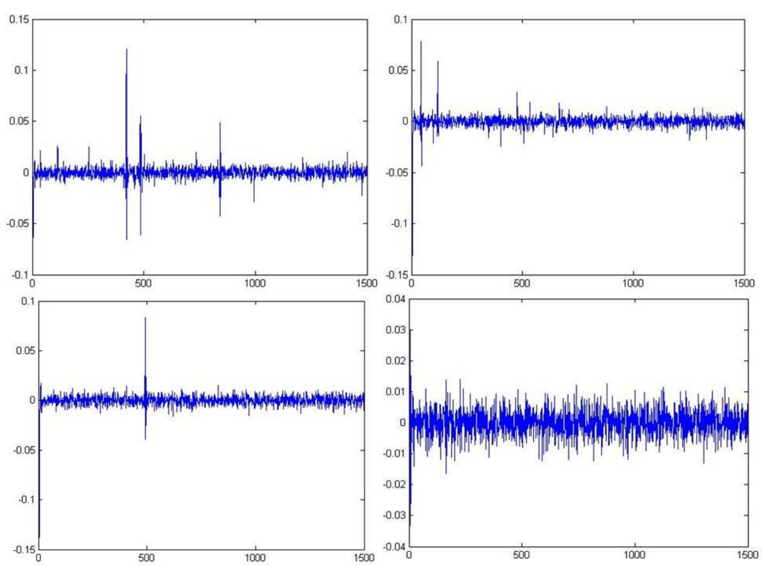

Fig. 3. Log-returns generated by the model; compare with Fig. 1

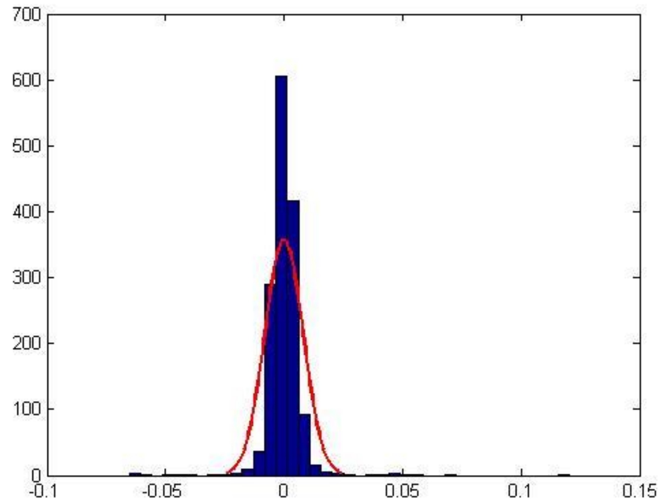

Fig. 4. The model return histogram and Gaussian fit; compare with Fig. 2

We are thus confident to proceed and explore some numerical implications of our model. Table 2 shows selected simulation results using NetLogo (http://modelingcommons.org/browse/one_model/3985#model_tabs_browse_procedures) for the benchmark case where all 10,000 agents are disposition-effect investors. We first assume $\omega = 1$ and $\bar{x} = 0.16$. Excess kurtosis abates and the market becomes more Gaussian as we add more groups with distinct return targets (as we increase i). Thus, greater diversity of return targets contributes to market efficiency, if Gaussianity can be translated into market efficiency [7]. Kaminski and Lo [4] proved stop-loss strategies cannot generate any excess profits if returns are i.i.d., and the (weak) efficient market hypothesis assumes a white noise in the distribution of returns. In our model, if we drop the disposition effect from the model, returns become Gaussian. The very existence of disposition-effect investors makes it possible for stop-loss investors to profit. In a non-Gaussian environment, which occurs when the disposition effect is considered, we find the stop-loss rule to further contribute to market inefficiency.

Table 2. The model returns when all the agents are disposition-effect investors.

Stop-loss investors	*i*	*Excess kurtosis*	*Jarque–Bera test*	*Lilliefors test*	*Reject normality?*
0	2	25.7	0.0000	0.001	Yes
0	3	21.2	0.0000	0.001	Yes
0	4	12.4	0.0000	0.001	Yes
0	6	6.7	0.1745	0.138	Yes
0	8	3	0.3880	0.186	No
0	12	2.9	0.3614	0.190	No
0	16	2.9	0.3516	0.235	No
0	32	2.9	0.3022	0.117	No

Table 3 shows the effect of the introduction of stop-loss agents who have the same $\bar{x}$. Now the agents cannot contribute to make the market more Gaussian. With $i > 4$, however, we cannot reject return normality. The presence of stop-loss agents reduces the importance of the disposition effect in such a non-Gaussian environment. As observed, in Ref. [4] stop-loss rules cannot stop losses for Gaussian returns, but are effective for non-Gaussian ones. Our model confirms this. Starting from an endowment, agents using the stop-loss rule profit constantly, while others are subject to both gains and losses.

Table 3. The model returns after the introduction of stop-loss investors.

Stop-loss investors	*i*	*Excess kurtosis*	*Jarque–Bera test*	*Lilliefors test*	*Reject normality?*
5	4	16	0.0000	0.0010	Yes
10	4	16	0.0000	0.0200	Yes
20	4	22	0.0000	0.0010	Yes
30	4	23	0.0000	0.0010	Yes
40	4	14	0.0000	0.0010	Yes
50	4	10	0.0000	0.0010	Yes

Our model recalculates the market sentiment index for each of the 50 periods. A once-and-for-all negative shock of -20 to I can make the stock price dip, after 100 periods, from 116 to 99. As a result, trade volume grows (Fig. 5). The reverse is true for a positive shock.

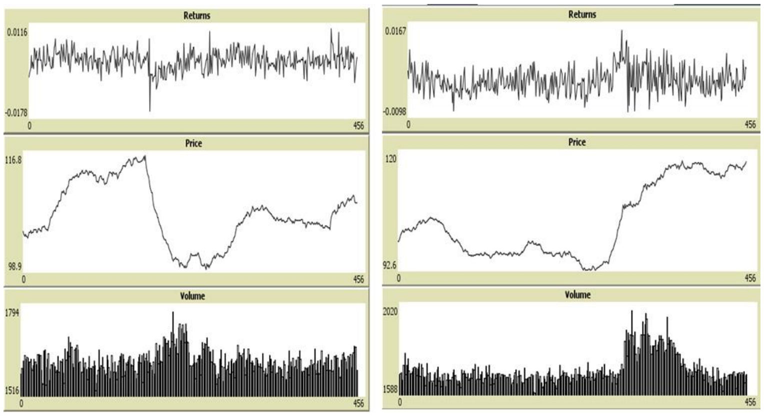

Fig. 5. Effects of shocks coming from the market sentiment index I

Fig. 6 shows the effect of overconfident agents as ω_i increases. Considering 25 percent of stop-loss investors and $i = 4$, as ω_i rises, both price and volume increase. As a result, overconfidence, which is accompanied by larger trade volume does not necessarily translate into losses for the investors. This is because the volume increase is not due to the disposition-effect, and the stop-loss agents are not affected by changes in ω_i.

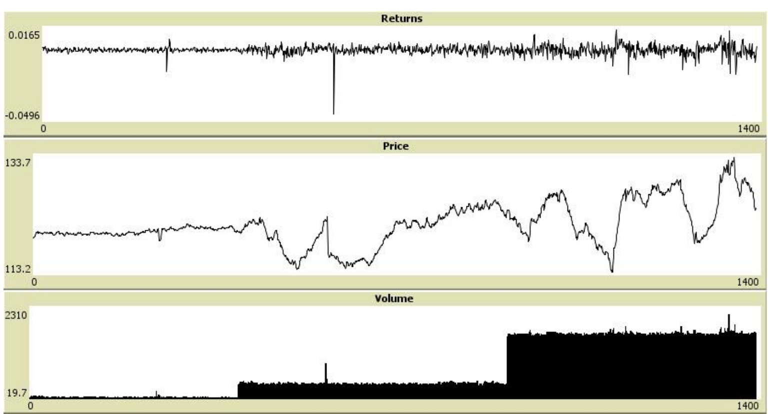

Fig. 6. The effect of overconfidence as ω_i increases from 0.1 to 1 and then to 10

The 10 simulation results in Table 4 show that the two groups of agents behave in tandem. The stop-loss agents keep winners 20 percent longer than the disposition-effect agents. And the stop-loss agents also sell the losers 53 percent faster.

4. Conclusion

We set up a model of the stock market that considers agents subject to the disposition effect and an offsetting stop-loss rule. The model can replicate actual return behavior considering data from the recent mini flash crashes. We explore the consequences of altering key behavioral parameters and show that differing return targets contribute to market efficiency; that a negative shock to the market sentiment index causes the stock price to dip and trade volume to grow; and that increasing overconfidence generates higher trade volume. More importantly, the presence of stop-loss agents in a non-Gaussian environment offsets the disposition effect.

Table 4. Offsetting the disposition effect

Simulations with 1,000 periods each	*Disposition-effect agents: number of periods keeping winners*	*Disposition-effect agents: number of periods keeping losers*	*Stop-loss agents: number of periods keeping winners*	*Stop-loss agents: number of periods keeping losers*
1	196	408	283	88
2	190	381	266	84
3	348	220	181	457
4	119	240	136	85
5	148	364	236	63
6	137	326	175	170
7	260	198	238	296
8	194	394	251	191
9	136	227	177	41
10	202	482	372	40
Average	**193**	**324**	**231**	**151**

Conflict of Interests

The author declares that there is no conflict of interests.

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