The Effects of Short-Selling and Margin Trading: a Simulation Analysis

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Abstract

This paper examines the effects of introducing and removing short sale constraints and margin requirements on a stock market using a multi-agent simulation model. We focused on the influence of these kinds of restrictions on daily price volatility and on traders long-run wealth distribution. We performed analysis both in a closed market and in an open market, where there is random cash inflow or outflow ten simulation days apart. Considering the closed market, we found that if short selling and margin trading are not banned, volatility tend to slightly increase. Also, we found that, if short selling and margin trading are allowed, there is a chance that some traders declare bankrupt and leave the market. Generally, the open and the closed market have similar features, except for the fact that in an open market the number of bankrupts increases. External factors, such as sudden variations of prices and wealth, damage traders who are in debt positions much more than the other traders.

1 Introduction

After the great stock market crash of 1929, some restrictions were implemented to ensure the market does not crash again. On one hand, when prices declined, many investors who had bought stocks on margin tried to sell their shares disrupting the market. On the other hand, short sellers were pointed out as one of the main causes of the crash. The U.S. stock market reacted restricting short-selling and setting margin requirements.

In 1934 the U.S. Congress gave the Federal Reserve Board the power to set initial, maintenance and short sale margin requirements on stock markets. Margin requirements were set in order to reduce excessive volatility of stock prices, protect investors from losses due to speculative activities, and reduce loans by banks to stockholders, moving credit toward more productive assets.

The 1987 stock market crash renewed both political and academic interest on the effectiveness of restriction policies for stocks and derivative products. Since then, a wide debate on these solutions started, and studies were performed on the effects of such impositions.

In April 2005, the China Securities Regulatory Commission (CSRC) issued a new plan for state share reform. As reported by Bloomberg News[2], *"China*

[2]For more details see http://www.bloomberg.com

plans to allow investors to take out loans to buy shares and to sell borrowed stock for the first time, moves aimed at tapping the country's $4 trillion of bank deposits and boosting trading. The China Securities Regulatory Commission may select five brokerages to start margin-lending and short-selling services this year". This event will surely renew the interest on short-selling and margin requirements regulations.

Buying on margin means to borrow money from a bank or a broker-dealer to buy securities. The margin requirements set the maximum legal amount that an investor may borrow to increase her/his purchasing power, so s/he can buy securities without fully paying for them. For instance, if the initial margin requirement is set at 20 percent, an investor can borrow up to 80 percent of the current value of the owned securities.

There has been an heated debate on the effectiveness of margin regulations and on their influence on asset prices. The central issue is the claim that margin requirements have an influence on stock price volatility.

In late eighties, some studies by Hardouvelis [5], [6] claimed that there is evidence of a negative relationship between stock volatility and margin requirements. Moreover, he asserted that changes in margins level can influence monthly stock return volatility. These conclusions support the opinion that margin requirements could be used to control price volatility.

On the other hand, previous literature disagree with Hordouvelis' findings. In 1966 Moore [19] stated that margin requirements fail to fulfil their objectives. Lanrgay and West [14] and Officer [21] also concluded that changes in margin requirements had little or no effect on stock price volatility.

Owing to the results of Hardouvelis, the debate on margin requirement effectiveness has become very heated. Many authors, including Salinger [24], Ferris and Chance [4], Schwert [25] and Hsieh and Miller [9], re-examined the connection between margin and volatility. These authors examined the issue from different points of view using different econometric techniques, but they uniformly concluded that there is no evidence of a relationship margin-volatility. Kenneth and Oppenheimer [11] tested whether margin requirements affect individual wealth-constrained speculators. To test this possibility, they examined the stock market reaction to changes in the initial margin requirement of the Tokio Stock Exchange. The analyzed the volatility of the stocks with the highest percentage of individual ownership, but they found, finding that changes in initial margin requirement don't have much effect on the volatility of those securities.

The impact of margin requirements on prices and volatility is an interesting issue, and the debate is still open.

Another critical question in financial literature, that is fairly symmetrical to margin trading is whether and how short-sale constraints affect the tendency of the stock markets.

Short selling is a technique used by investors who try to profit from the falling price of a stock. They borrow the shares from someone else and sell them. When the price falls, they will cover their position by buying back the shares. If their prediction was right, short sellers gain a profit.

After the stock market crash of October 1929, many short-sale restrictions were imposed on short-selling in the United States. Short sellers were immediately pointed out as the cause of the collapse, so three regulatory changes were decided in order to reduce short-selling [3].

Short-selling advocates claim that it increases liquidity, favours risk sharing and increases informational efficiency. On the other hand, opponents of short-selling claim that it causes high volatility, favors market crashes and panic selling.

In 1977 Miller [18] observed that, if short-selling is restricted and investors have heterogeneous beliefs, the observed price of a security does not reflect the beliefs of all potential investors, but only the opinion of the optimistic ones. The implication of his idea was that stocks may be overpriced because of short-selling restrictions. Miller's hypothesis implies a negative relationship between short interest and returns. In recent years, empirical evidence on this relationship has been pointed out by several studies, among them we cite Jones and Lamont [10], Ofek and Richardson [20] and Chen [2].

King et al. [12] studied the effect of short selling on asset market bubbles in an experimental laboratory environment. found that short selling does not influence market bubbles. Ackert et al. (2001) [1] conducted experiments on two asset markets and stated that short selling eliminates the bubble-and-crash phenomenon. Haruvy and Noussary [7] studied the relationship between short-selling constraints and assets prices using a simulation model based on DeLong's work [15]. They found that short selling reduces prices to levels below fundamental values and that the reduction of the bubble-and-crash phenomenon is the consequence of such a trend rather than of the effectiveness of short selling restrictions.

Some studies examine the relationship between return volatility and short-sale constraints. Ho [8] produced evidence that volatility increased when short-selling prohibition was lifted during the Pan Electric crisis of 1985. Kraus and Rubin [13] developed a model to predict the effect of index options introduction on volatility of stock returns. Since short-selling the stock was restricted, the option was considered as a form of reduction of this constraint. The model is highly stylized, and it predicts that volatility can either increase or decrease, depending on model parameters.

Diamond and Verrecchia [3] asserted that short-sale restrictions can slow down the response of prices to new information: some investors who want buy or sell cannot take part in the market bringing a decline in liquidity. In other words, if short-selling is possible, there is greater liquidity.

There is not a widely accepted theory on the effects of short-sale restrictions on price volatility, and the reactions of stock markets to the imposition of margin requirements and of short-selling restrictions are still not fully understood. So, rules and regulations could be implemented without a clear understanding of their potential impact.

In this paper, we contribute to the debate and propose a multi-agent model for analyzing the effects of introducing and removing these kinds of restrictions on a stock market. Our aim is to study whether and how stock prices, volatility and long-run wealth distribution are influenced by these restrictions. Our model is agent-based, and only one stock is negotiated in the market.

The introduction and the removal of constraints enabled us to analyze some interesting issues:

- Effects of restrictions on volatility

[3] For more details see http://www.prudentbear.com/press_room_short_selling_history.html

- Long-run wealth distribution
- Relationship between price shocks and *in debt positions*

The remainder of the paper is organized as follows: section 2 describes the details of the proposed model. Section 3 illustrates how margin requirements and short selling restrictions influence a closed market describing the most important findings. Section 4 shows the results for an opened market, and section 5 concludes this study, recapitulating the key findings.

2 The Model

In our research we developed a multi-agent model for analysing the effects of introducing and removing margin and short-sale restrictions on an artificial financial stock market, using a simulation approach.

The simulation model has been developed on the basis of the *Genoa Artificial Stock Market* (GASM) core [22], [23]. Since one of the ultimate goals of our work is to develop a general framework for financial market simulation, we have re-engineered the original GASM, in order to extend its features and to adapt it to our needs. Results on the re-engineered GASM have been presented in [16] and [17]. The structure of our model is characterized by a market in which N agents trade a single stock that does not pay any dividend. Each trader is modeled as an autonomous agent, and s/he is endowed with a limited amount of cash and stocks. The agents are divided into sub-populations that adopt different trading strategies, and each trader issues orders based on her/his own trading strategy.

At the beginning of each simulation, cash and stocks are distributed among agents following a Zipfs' law. At each time step t, corresponding roughly to one trading day, each trader issues a limit order with a given probability p, usually set at 10% for each trader. The pricing mechanism of the stock is based on the intersection of the demand-supply curve [23].

Both margins and short-selling restrictions are implemented in a simplified manner. We don't distinguish between initial margin requirements and maintenance requirements. There are no transaction costs or taxes, so agents can borrow money/stocks without paying any interest for them. Moreover, margin and short-selling requirements are kept symmetrical, in the sense that their maximum allowed percentages are the same.

The population of traders is made up of two main categories: the first one consists of agents that can issue orders using their available limited resources. They are forbidden to sell if they do not have any stock to sell, and they cannot buy if they do not have enough money to do so. The second one is made up of traders that are allowed to buy/sell stocks in debt. The agents can sell stocks without owing them (we will say that they can issue *in debt selling orders*) and buy shares without owing enough money to pay them (*in debt buying orders*). We will name agents belonging to the second group *Debt Prone Traders* (DPT), and we will call agents from the first group *non-Debt Prone Traders* ($non-DPT$). Both DPT and $non-DPT$ belong to one of four categories of traders: random traders, fundamentalists, momentum and contrarians traders. For the sake of brevity we will mark DPT traders with a star (for instance Random* means "Debt Prone Traders of type Random").

Random Traders

Random traders are characterized by the simplest trading strategy. They are traders with zero intelligence who issue random orders. Random traders represent the bulk of traders who trade for reasons associated with their needs and not with market behavior. If a random trader decides to issue an order, it may be a buy or sell limit order with equal probability.

Fundamentalist Traders

Fundamentalists strongly believe that each asset has got a fundamental price (p_f) related to factors external to the market and, sooner or later, the price will revert to that fundamental value. The fundamental price is the same for all fundamentalists. If a fundamentalist decides to trade, s/he places a buy (sell) order if the current price ($p(t)$) is lower (higher) than the fundamental price p_f. At each time step, fundamentalists decide whether or not to trade with a probability p depending on the ratio between p_f and $p(t)$. If $p(t) = p_f$, the probability p will be equal to 0.0, and it will increase as a squared function of the ratio $max(\frac{p_f}{p(t)}, \frac{p(t)}{p_f})$. The maximun value of p is set at 0.1. Note that, if the price of the asset is close to p_f, the trading activity of fundamentalists is low, because the market is not very attractive for them.

Momentum Traders

Momentum traders are trend-followers. They play the market following past price trends, and strictly rely on price information. Momentum traders buy (sell) when the price goes up (down). They represent, in a simplified way, traders following technical analysis rules and traders following a herd behavior. A time window (τ_i) is assigned to each momentum trader at the beginning of the simulation through a random draw from a uniform distribution of integers in the range from 2 to 10 days.

Contrarian Traders

Contrarian traders are trend-followers too, but they speculate that, if the stock price is rising, it will stop rising soon and fall, so it is better to sell near the maximum, and vice versa. A time window (τ_i) is assigned to each contrarian trader at the beginning of the simulation in the same way as for momentum traders.

2.1 non-Debt Prone Traders

$non - DPT$ are risk-adverse agents, so they trade using their limited resoures without issuing *in debt orders*. If a *non debt prone* trader issues a buy (sell) limit order, the order amount is computed at random, and the limit price is computed multiplying (dividing) the current price by a random number drawn from a Gaussian distribution $N(1, s_i)$. The average of the distribution $N(1, s_i)$ is 1.0, and the standard deviation s_i depends on the historical market standard deviation, $\sigma_i(\tau_i)$, computed on a past price series whose length (τ_i) is set at 10, according to equation 1:

$$s_i = k * \sigma_i(\tau_i) \tag{1}$$

where k is a multiplying factor which is set at 1.4.

2.2 Debt Prone Traders

DPT are risk-prone agents. They can borrow money (or stocks) without paying any interest on it (there are no transaction costs or taxes), but in debt transactions must be guaranteed by the agents' total wealth. The debt level of each *DPT* cannot exceed a certain threshold called *safety margin* (m). If a trader exceeds the *safety margin* s/he is forced to cover her/his position and repay her/his debts. If an agent has negative wealth $w_i(t)$, s/he goes bankrupt and is obliged to leave the market. The wealth $w_i(t)$ of the generic trader i at time step t is defined as $w_i(t) = c_i(t) + a_i(t) \cdot p(t)$, where $c_i(t)$ is the amount of cash and $a_i(t)$ the amount of stocks that the agent i holds at time t. The *safety margin* is a constraint that can be moved up or down in order to allow agents to borrow more or less money (stocks), setting the debt limit. In our tests, the value of m varies from 0.0 to 0.9. If $m = 0.0$, it means that both short selling and margin trading are forbidden. If $m > 0.0$, it means that short selling and margin trading are allowed. For instance, if m is set at the maximum value (0.9), it means that margins are set at 10% and a debt prone trader can borrow stocks (to sell short) or cash (to buy on margin) up to 90% of her/his cash (stock value). Each debt prone trader decides whether to buy or sell first on the basis of her/his strategy, then s/he has two choices: to trade using her/his limited resources or to trade borrowing stocks or money. These choices have equal probability.

If the agent i decides to issue an *in debt order*, the order size has an upper limit. If the agent issues a buy order, the amount of stocks to purchase cannot exceed the quantity $\hat{a}_i^b(t)$ (see equation 2). *In debt selling orders* are generated fairly symmetrically relative to *in debt buying orders*, the maximum quantity on sale is $\hat{a}_i^s(t)$ (see equation 3).

$$\hat{a}_i^b(t) = m \cdot a_i(t) + \lfloor \frac{c_i(t)}{p(t)} \rfloor \tag{2}$$

$$\hat{a}_i^s(t) = a_i(t) + \lfloor m \frac{c_i(t)}{p(t)} \rfloor \tag{3}$$

where $p(t)$ is the asset price, $c_i(t)$ represents the amount of cash and $a_i(t)$ the amount of stocks that a generic agent i holds at time t

If an agent exceeds her/his *safety margin*, s/he is obliged to cover her/his position. In particular, if s/he holds an amount of assets $a_i(t) < 0$ and $\hat{a}_i^s(t) < 0$, she/he is forced to buy the amount of stocks equal to the quantity expressed in equation 4. Symmetrically, if a trader holds an amount of cash $c_i(t) < 0$ and $\hat{a}_i^b(t) < 0$, she/he is forced to sell an amount of stocks equal to the quantity expressed in equation 5.

$$a_m^b = \lceil -\frac{a_i(t) + m\frac{c_i(t)}{p(t)}}{1-m} \rceil \tag{4}$$

$$a_m^s = \lceil -\frac{m \cdot a_i(t) + \frac{c_i(t)}{p(t)}}{1-m} \rceil \quad (5)$$

3 Results - Closed Market

First, we performed several computational experiments on a closed market, i.e. a market with no cash or stock inflow or outflow. We performed several tests varying some parameters of the model such as the percentage of DPT and $non-DPT$ agents, the percentage of the four population types, the safety margin and the probability that DPT traders issue in debt orders. We considered a large number of experimental cases, performing 20 runs for each case. Each simulation is usually run with 4000 time steps (corresponding to a time span of 20 years) and with 400 agents. A time step represents one day of trading. The initial endowment of traders (both in cash and stocks) was obtained by dividing agents into groups of 20 traders, and applying Zipf's law to each group. We found that an unequal initial endowment increases trading volumes and generates logarithmic returns with fatter tails. Note that in the real world market traders' wealth is unequally distributed. In our model, each trader is endowed with an average \$50000 cash and with an average 1000 stocks. At the beginning of the simulation, the starting price of the asset is set at a value equal to the total wealth divided by the number of assets (\$50), which amounts to the "equilibrium" value for prices

Random Traders

We first explored market behavior when only random traders are present. We studied volatility trend varying some parameters of the model. Volatility is defined as the standard deviation of prices in a time window 50 steps long. We set the Safety Margin at 0.8 and varied the percentage of Random* traders from 0% to 100% in steps of 25%. The results showed that an increase in the percentage of random traders able to trade in debt brings a very slight increase in volatility, as shown in figure 1.

We also explored return volatility varying the value of m parameter from 0.1 to 0.9. We observed that volatility looks not affected by m, but for the highest values of m. This result does not depend on the percentage of $DPTs$. In figure 2 we report this behavior for simulations with 50% of debt prone traders. When $m = 0.9$, there is an increase in volatility, but this phenomenon is due to the bankrupt of some traders, which makes the market unstable. When a trader goes bankrupt, s/he is forced to cover her/his position as far as possible, and then s/he leaves the market. This fact, on one hand implies that an amount of stocks are sold or bought at limit prices low or high enough to have a high probability to be fulfilled, and on the other hand lowers the number of traders. Both effects tend to increase market volatility.

We found similar results by varying the probability that $DPTs$ issue in debt orders, as shown in figure 3. This behavior is not unexpected, because increasing this probability is equivalent to increase the percentage of in debt orders; with a high margin equal to 0.8, this yields many bankrupts, with consequent volatility increase.

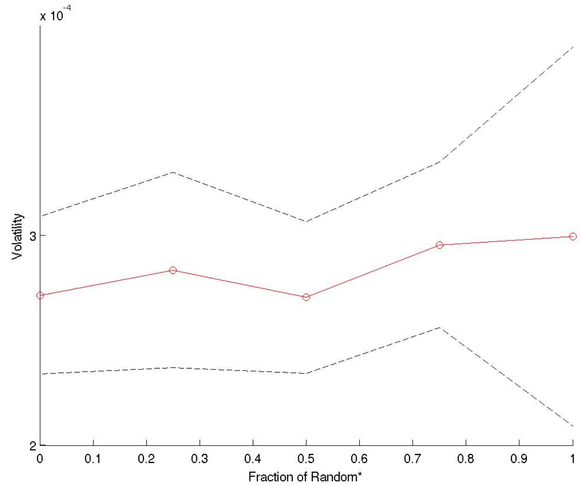


Figure 1: *Mean and standard deviation of price variance as a function of Random*. The percentage of DPT was varied from 0% to 100% in steps of 25%, with* $m = 0.8$.

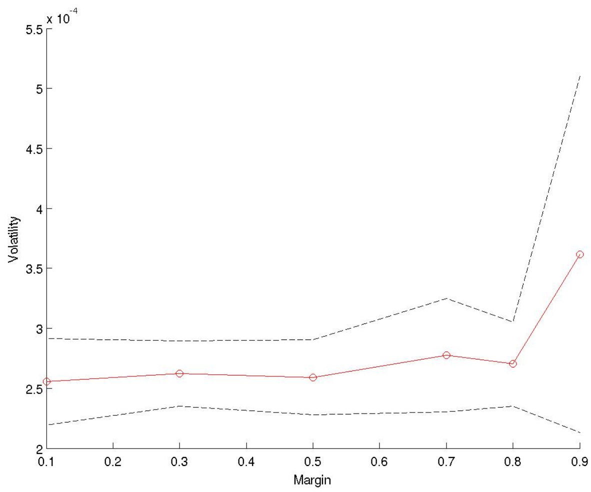


Figure 2: *Mean and standard deviation of price variance as a function of* m.

We also studied the dynamics of wealth of the populations of traders. The wealth $w_i(t)$ of trader i at time step t is defined as the sum of her/his cash and the value of her/his stocks at the current price: $w_i(t) = c_i(t) + a_i(t) \cdot p(t)$. We found that the wealth of both random and random* traders remains approximately the same during the whole simulation. Figure 4 shows the average wealth $1/N \sum_i w_i(t)$ of the two populations for a typical simulation 4000 steps long with 50% random and 50% random* traders. The total traders' wealth varies, depending on the stock price variations, but the wealth of both populations does not differ significantly for the whole simulation.

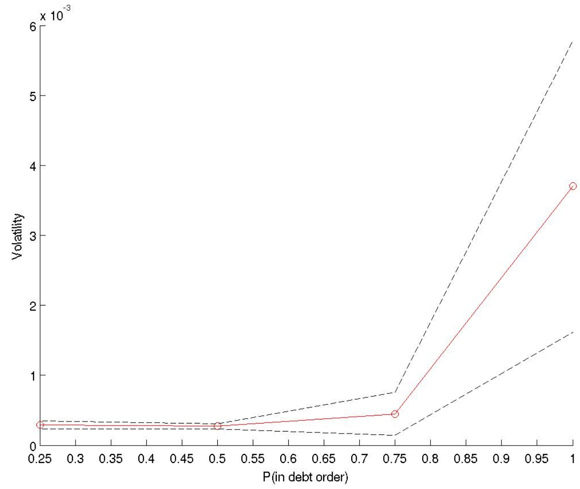


Figure 3: *Mean and standard deviation of price variance as a function of P(in debt order), with the percentage of DPT radom traders set at 50% and* $m = 0.8$.

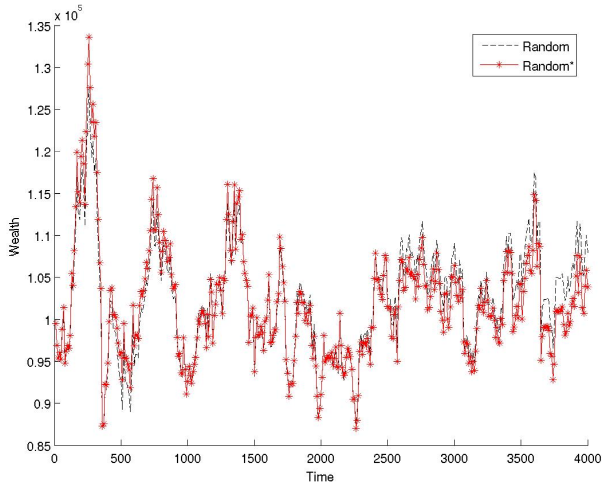


Figure 4: *Dynamics of wealth of Random and Random* for a typical simulation with* $m = 0.8$ *and* $P(indebt) = 50\%$.

Trend Followers

Next, we investigated how volatility is influenced by the presence of trend followers (momentum and contrarian) debt prone traders. We performed six groups of tests: Random and Momentum; Random and Momentum*; Random and Contrarian; Random and Contrarian*; Random, Momentum and Contrarian; Random, Momentum* and Contrarian*. The total percentage of trend followers has been set to 0, 10% and 20%. When there are both momentum and contrarian traders, each kind accounts for one half of the total percentage. Each value shown is the mean of 20 runs. The standard deviation of market volatility in these runs is shown in parenthesis.

Table 1 reports the results for the various kinds of trend followers. First, we found that the presence of a small percentage of momentum traders alone (up to about $10-15\%$) does not tend to increase volatility, that increases only for higher percentages. This is probably due to the limited amount of traders' resources, and to the different time scales the momentum traders use to compute the trend. This behavior is similar with debt prone momentum traders (Momentum*), but when they reach 20%, volatility sudden increases. This is due to a not negligible number of traders who declare bankrupt, with consequent increase in volatility.

In the performed simulations, the presence of contrarian traders alone tend to slightly increase volatility. This phenomenon is still not completely clear, but is probably due to the "hits" to the price in the opposite direction of the current price trend. This phenomenon is not affected by limited traders' resources, because it is in accord with the intrinsic mean reversion behavior of prices. The presence of debt prone contrarian traders obviously increases this behavior. When debt prone contrarian traders reach 20%, there are very few bankrupts, that further slightly increase volatility.

When both kinds of trend followers play together, the situation stabilizes, irrespectively of their debt inclination. Market volatility tends to be constant, and in this case we did not observe any bankrupt.

Table 1: *Mean and Standard Deviation of volatility with trend followers and random traders. The results are multiplied by* 10^3.

	0%	**10%**	**20%**
Momentum	0.27 (0.04)	0.26 (0.04)	0.30 (0.04)
Momentum*	0.27 (0.04)	0.29 (0.04)	0.94 (0.41)
Contrarian	0.27 (0.04)	0.31 (0.04)	0.45 (0.06)
Contrarian*	0.27 (0.04)	0.35 (0.06)	0.59 (0.11)
Momentum and Contrarian	0.27 (0.04)	0.27 (0.02)	0.25 (0.03)
Momentum* and Contrarian*	0.27 (0.04)	0.28 (0.03)	0.27 (0.03)

We then analyzed the effects of the dynamics of wealth with the trend follower traders. In a previous work [16], we showed that contrarian traders gain wealth at the expenses of momentum traders and of random traders. We investigated if and how DPT agents influence this behavior. We found that debt prone traders show the same dynamics of $non-DPT$ traders, but the effects are amplified. Contrarian* traders gain more than Contrarian traders, Momentum* lose more than Momentum traders, as shown in figure 5.

Fundamentalists

When studying volatility behavior using random traders and fundamentalist traders, we found that allowing fundamentalists to short sell and to buy on margin volatility increases. Table 2 shows the market volatility (and its standard deviation, related to 20 different runs), setting the total percentage of fundamentalists to 0, 10% and 20%. Note that no trader declares bankrupt during all simulations. In all cases, the total wealth of both fundamentalists and debt prone fundamentalists tend to increase at the expenses of random traders' wealth.

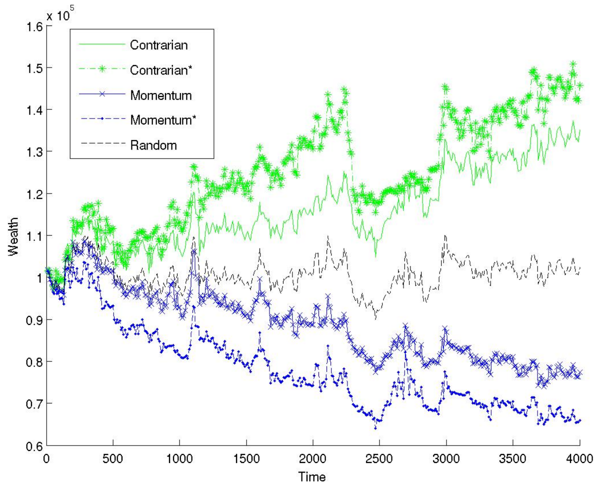
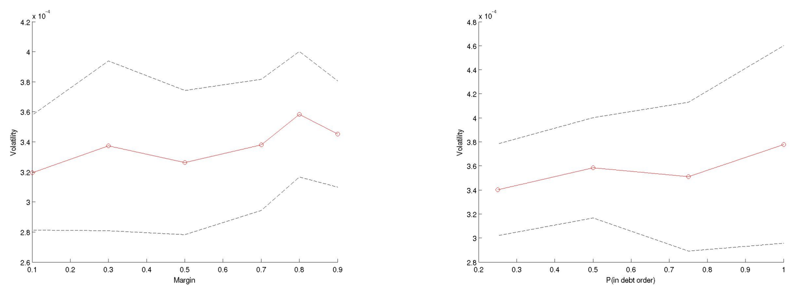


Figure 5: *Dynamics of wealth with trend followers for a typical simulation with* $m = 0.8$ *and* $P(indebt) = 50\%$.

Figure 6 shows that volatility slightly increases with the increase of the safety margin m and of the probability that debt prone traders issue a debt order $P(indebt)$.

Table 2: *Mean and Standard Deviation of volatility with fundamentalists and random traders. The results are multiplied by* 10^3.

	0%	**10%**	**20%**
Fundamentalist	0.27 (0.04)	0.33 (0.04)	0.51 (0.10)
Fundamentalist*	0.27 (0.04)	0.36 (0.04)	0.55 (0.11)



(a) *Volatility as a function of the Safety Margin.*

(b) *Volatility as a function of P(in debt).*

Figure 6: *Volatility with a population made of 10% of DPT fundamentalists and of 90% random traders.*

All Kinds of Traders

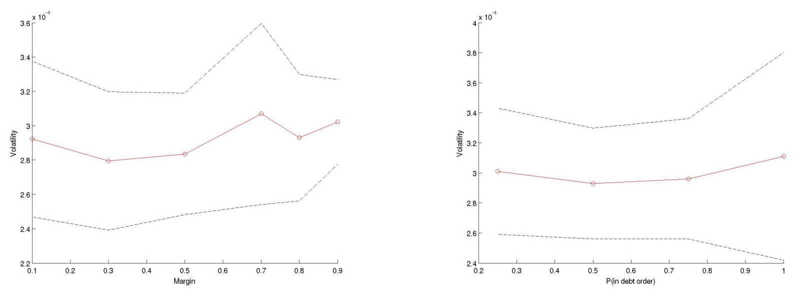
In this section we report the results of tests we conducted using all trader populations. The main goal was to understand whether or not the results were merely the sum of the effects of each population.

First, we used momentum, contrarian and fundamentalist traders, setting the same percentage of agents for each kind of strategy. We found that DPT traders slightly increase volatility, as shown in table 3. In this table, the reported percentages refer to each kind of traders. So, a percentage of 5% means that there are 5% of fundamentalists, 5% of momentum and 5% of contrarian traders.

Table 3: *Mean and Standard Deviation of volatility with fundamentalists trend followers and random traders. The results are multiplied by* 10^3.

	0%	**5%**	**10%**
Fundamentalist, Momentum, Contrarian	0.27 (0.04)	0.28 (0.04)	0.34 (0.06)
Fundamentalist*, Momentum*, Contrarian*	0.27 (0.04)	0.29 (0.04)	0.38 (0.07)

Note that the increase in volatility is not due to failures of traders, because no trader fails during any of these tests. The sensitivity analysis both of the m parameter and of the the probability that debt prone traders issue a debt order show results similar to those presented in previous sections. The findings are shown in figure 7.



(a) *Volatility as a function of the Safety Margin.*

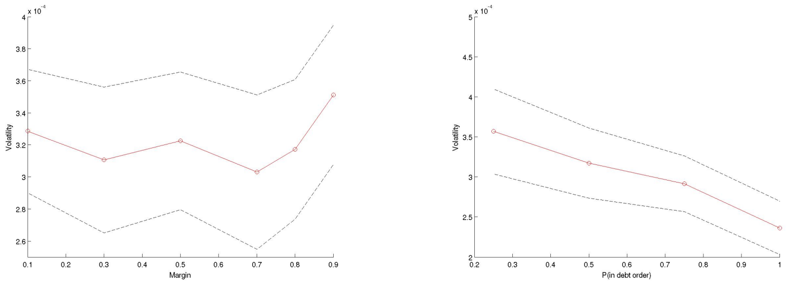
(b) *Volatility as a function of P(in debt).*

Figure 7: *Volatility with a population made of 5% of DPT fundamentalists, 5% of DPT momentum and 5% of DPT contrarian traders.*

Finally, we performed a group of tests using all kinds of traders, with and without PDT. We set the percentage of both DPT and $non-DPT$ fundamentalist, momentum and contrarian traders at 5%, and the percentage of both DPT and $non-DPT$ random traders at 35%. We chose to equally divide the *thermal bath* of agents of type random into 2 populations of the same size of DPT and $non-DPT$ agents in order to avoid any kind of asymmetry in the results. The resulting volatility was 0.31, with a standard deviation of 0.04. This figure has to be compared with the case of a market with no debt prone trader, but with the same percentage of fundamentalist, momentum and contrarian traders with respect to random ones. In this latter case, we had a volatility pf 0.28, with a standard deviation of 0.04. In both cases, there is no trader declaring bankrupt.

The sensitivity analysis referring to this case is shown in figure 8. Here volatility looks to slowly decrease with m, except for the highest values. The most interesting result is that, with all kinds of traders playing the market, volatility clearly decreases with the probability that debt prone traders place in debt orders. This result is due to the interplay of all kinds of traders, and we don't have at the moment an explanation for it.

Figure 9 presents the wealth dynamicsfor a typical simulation in which all eight populations are taken into account. Note that fundamentalists and contrarians gain wealth, while momentum traders and, to a lesser extent, random traders, lose wealth. This behavior is due to the relationship between the strategies of each type of trader and the mean reverting behavior of the market [23]. The new finding is that debt prone traders present the same behavior of $non-DPT$, but they amplifies the effects obtained without them. Actually, fundamentalist and contrarian $DPTs$ gain more than fundamentalist and contrarian $non-DPTs$, while momentum and random $DPTs$ lose more than $non-DPTs$ of the same kind.



(a) *Volatility as a function of the Safety Margin.*

(b) *Volatility as a function of P(in debt).*

Figure 8: *Volatility with a population made of all types of traders, both DPT and $non-DPT$.*

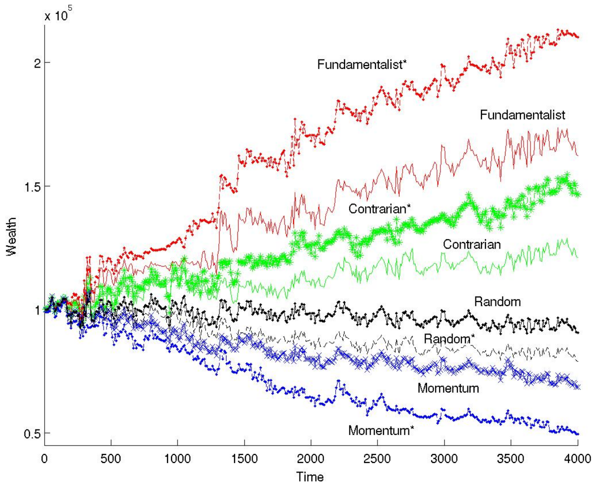


Figure 9: *Dynamics of wealth with all eight types of traders for a typical simulation with $m = 0.8$ and $P(indebt) = 50\%$.*

4 Results - Open Market

We opened the market by varying the cash of the traders. The main goal is to understand how external shocks influence volatility, both with and without $DPTs$. The cash variation $\Delta c_i(t)$ follows the law expressed in equation 6. $\Delta c_i(t)$ is proportional to each trader's wealth and its level depends on the σ parameter.

$$\Delta c_i(t) = w_i(t) \cdot [e^{N(0,\sigma)} - 1] \tag{6}$$

where $N(0, \sigma)$ is a random draw from a Gaussian distribution with average 0 and standard deviation σ, and σ is a parameter. These inflows and outflows of cash can be considered as external factors able to influence the market. We varied the amount of cash 10 steps apart, by adding to each trader's cash the term $\Delta c_i(t)$ defined in equation 6.

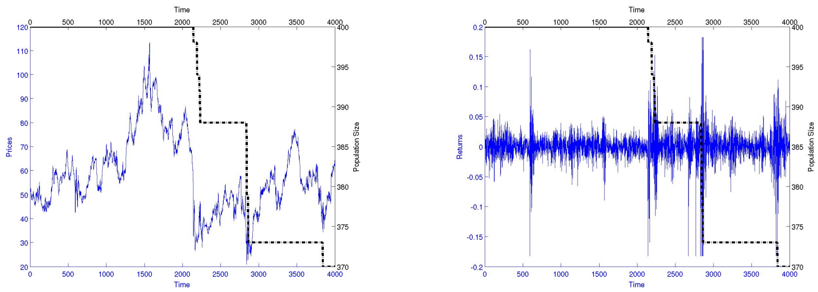
We performed many runs changing the population of traders. For the sake of brevity, we report here just two examples: the first one with random traders and the second one with all kinds of traders. The findings are similar to those obtained using other combinations of traders.

The main result is that changes to traders' cash increase volatility. The increase is patient both with and without DPT traders. Table 4 shows this finding for tests conducted with $non-DPT$ random traders and with a population made up of 50% $non-DPT$ and of 50% DPT random traders. Note that if $DPTs$ are present, volatility will increase more than without them. Also, if the value of σ is too high, volatility will suddenly increase. We studied the last case (reported in the last column of table 4) more deeply, and we found that the excessive increment in volatility is due to a sudden increase in the number of traders who fail.

The quantity of traders who declare bankrupt can be inferred from figure 10, which shows the total number of traders active in the market versus simulation steps. An excessive cash inflow can destabilize the market. Even if $DPTs$ are not present, a large number of agents can fail and leave the market, because of negative cash inflows. This phenomenon yields an increase in price returns and in volatility. Figure 10 shows the population size superimposed on prices and the population size superimposed on logarithmic returns for a simulation with random traders alone, and $\sigma = 10^{-4}$. These figure show a correspondence between the steps where traders' failures happen, and daily return variations, which look very high during these steps.

Table 4: *Mean and Standard Deviation of Volatility with random traders. The results are multiplied by* 10^3

Population		σ		
Random	**Random***	0.0	10^{-5}	10^{-4}
100%	0%	0.27 (0.04)	0.29 (0.05)	1.99 (1.48)
50%	50%	0.27 (0.03)	0.29 (0.06)	6.19 (4.53)



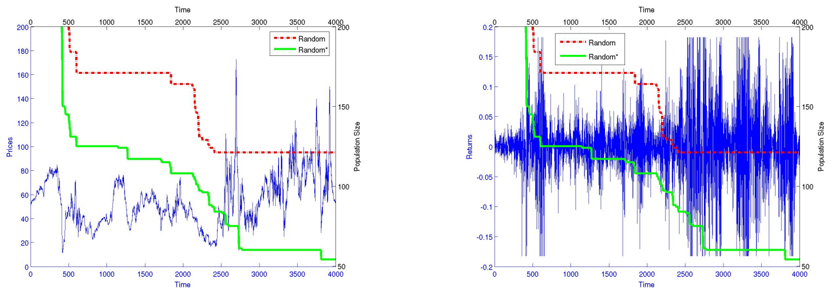
(a) *Population size superimposed on prices.*

(b) *Population size superimposed on returns.*

Figure 10: *Daily time series for prices (left) and returns (right) with random traders and* $\sigma = 10^{-4}$. *The dotted line represents the population size.*

If $DPTs$ are present, the number of agents who decleare bankrupt increase. Also, these traders tend to fail sooner. We calculated the number of failed traders after the end of the simulations, and we found an average of 150.95 bankrupts in the case of random traders alone (with standard deviation 71.00). If random $DPTs$ are taken into account, the average number of traders who leave the market increase to 239.10 (with standard deviation 107.78). Figure 11 shows the relationship between traders' bankrupts, prices and returns. In order to remark that debt prone traders tend to fail more than $non-DPTs$, figure 11 reports the population size of both random and random* traders. Note that, if the number of failures is too high (over 50%), the market will become unsteady. Moreover, in the case of open market, the results are robust to changes in the values of the safety margin and of $P(indebt)$.

We conducted further experiments using different traders' populations, as the ones described in section 3. We found similar results to those obtained with only random traders – cash inflows and outflows increase volatility, debt prone traders tend to declare bankrupt more frequently than $non-DPTs$ of the same kind, simulations are robust to changes in m and in $P(indebt)$.



(a) *Population size superimposed on prices.*

(b) *Population size superimposed on returns.*

Figure 11: *Daily time series for prices (left) and returns (right) with 50% $non-DPT$ and 50% DPT random traders, with $\sigma = 10^{-4}$. The dotted line represents the population size.*

5 Conclusions

In this paper we examined the effects of margin requirements and of short sale restrictions on a stock market using a simulation approach. We focused on the influence of introducing and removing these kinds of restrictions on daily price volatility and on traders' long-run wealth distribution. We performed analysis both in a closed market and in an open one. If restrictions are present, they are imposed both on short sales and on margin trading.

Considering the closed market, we found that if short selling and margin trading are allowed, volatility will tend to slightly increase. The increase in volatility is substantially unrelated to restriction levels and to debt proneness of traders. We found that, if short selling and margin trading are not banned, some traders could declare bankrupt and leave the market. The number of bankrupts is usually very low and negligible. Also, the wealth distribution of both $DPTs$ and of $non-DPTs$ have the same trend, but for $DPTs$ the trend is stronger.

We showed that generally the open and the closed market have similar features, except for the fact that in an open market the number of bankrupts increases. External factors, such as sudden variations of prices and wealth, damage $DPTs$ much more than $non-DPTs$, so $DPTs$ tend to fail more easily than $non-DPTs$. In general, bankrupts favor high volatility of prices and may lead to periods of unsteadiness, so we can assert that in this sense the presence of in debt positions may ease unsteadiness.

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