Using an Artificial Financial Market for Assessing the Impact of Tobin-like Transaction Taxes

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Abstract

The Tobin Tax is a solution proposed by many economists for limiting the speculation in foreign exchange and stock markets, and for making these markets stabler. In this paper we present a study on the effects of a transaction tax on one and on two related markets, using an artificial financial market based on heterogeneous agents.

The microstructure of the market is composed of four kinds of traders: random traders, fundamentalists, momentum traders and contrarians, and the resources allocated to them are limited. In each market it is possible to levy a transaction tax. In the case of two markets, each trader can choose the market where to trade, and an attraction function is defined which drives their choice, based on perceived profitability. We performed extensive simulations, and found that the tax actually increases volatility and decreases trading volumes. These findings are discussed in the paper.

1 Introduction

The deep financial crises of the last decade, starting from the Mexican pesos crisis in 1994 up to the Argentina one in 2001, raised serious doubts as to the ability of free markets to reflect the "true" value of a specific currency. In fact, too many speculative activities can produce a strong bias in exchange rates and create a monetary crisis, or at least amplify its effects. Many observers claim that a tax on currency transactions may prove a powerful tool for penalizing speculators and stabilizing markets. For these reasons, in recent years there has been an ongoing interest in the idea advanced by some economists (among

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whom the most famous is James Tobin - see Tobin (1978)) to levy a small tax on currency transactions.

Over the last thirty years the volume of foreign exchange trading has increased hugely. In 1973, daily trading volume averaged around \$15 billion; today, it averages \$ 300 billion. Moreover, 90% of the trading volume concerns short-term transactions. In general, economists believe that most short-term transactions are of a speculative nature, and many considered them to be a source of market volatility and instability. Instead, medium or long term transactions are usually related to real investments.

In 1936, Keynes in *The General Theory of Employment, Interest, and Money* (Keynes; 1936) asserted that the levy of a small tax on all stock exchange transactions should contribute to reducing instability in domestic stock markets. According to Keynes, this tax should discourage speculators from trading, resulting in lower price volatility of the taxed asset.

In 1978, the Nobel Prize Laureate in Economics James Tobin (1978) proposed the levy of a small tax (0.1%) on all foreign exchange transactions. This would penalize short-term speculators but not long-term investors, favoring market stability. Later, several authors (see, e.g. Palley; 1999a; Baker; 2000; Felix and Sau; 1996; Jeffrey A.; 1996; Kupiec; 1995) proposed a similar solution for other kinds of securities.

On the other hand, some economists disagree with Keynes and Tobin's views. Friedman (1953) challenged these theories arguing that speculative trading could stabilize prices.

There are only a few empirical analyzes on the effects of transaction taxes on price volatility. Umlauf (1993) studied Swedish stock market data and showed that the introduction of a Swedish tax increased the volatility of stock prices. Its worth noting that the tax level was set at 1% in 1984 and at 2% in 1986: such values are far too high compared with the percentage proposed by Tobin.

Habermeier and Kirilenko (2001) analysed the effects of transaction costs and of capital controls on markets, and showed that they can have negative effects on price discovering, volatility and liquidity, reducing the market efficiency. They produced evidence that the Tobin tax increases market volatility by discouraging transacting, thereby reducing market liquidity.

(Palley; 2003) argues that the Tobin tax is good for financial stability, and that the total transaction costs are not necessarily increased by the imposition of the Tobin tax. Actually, transaction costs could change the composition of traders, getting out short-term investors from the market. It leads to a reduction in volatility and consequently in total transaction costs.

Aliber et al. (2003) produced evidence that a Tobin tax on Foreign Exchange Transactions may increase volatility. They constructed the time series of monthly transaction costs estimates, volatility and volume, for four currencies (the British Pound, the Deutsche Mark, the Japanese Yen and the Swiss Franc) for the period 1977 to 1999. They showed that volatility is positively correlated with the level of transaction costs, while trading volume is negatively correlated. Their results suggest that an increase in transaction costs leads to a decrease in trading volume. Therefore, the effect of the tax on volatility is exactly the opposite of what the proponents of the Tobin tax would like to have seen. On the other hand, the findings of Aliber et al. (2003) were strongly criticized by Werner (2003), who argued that the direction of causality between tax and volatility/volumes may be in the opposite direction.

In *The effectiveness of Keynes-Tobin transaction taxes when heterogeneous agents can trade in different markets: a behavioral finance approach* Westerhoff and Dieci (2004 in press) developed a model in which rational agents apply technical and fundamental analyzes for trading in two different markets. Their model shows that, if a transaction tax is imposed in one market, speculators leave this market, making it less volatile. Therefore, their model confirms Tobin's hypothesis.

So, the debate on whether levying a small tax on each market transaction could help to reduce speculation and price volatility is still open. The reactions of stock markets to the imposition of margin requirements and of short-selling restrictions are still not fully understood, and rules and regulations could be implemented without a clear understanding of their potential impact. It is difficult to test the effects of restrictions on real markets empirically, and the simulation approach could help to understand these phenomena in a non invasive way.

In this paper, we contribute to this debate, and propose a multi-agent model for analyzing the effects of introducing a transaction tax on one and then on two related stock markets from a structural and behavioral perspective. Our aim is to study if and how market volatility and trading mechanism are influenced by a Tobin tax, and if and how traders change their strategies. Our model is agent-based, and only one asset is negotiated in each market. We developed a simulator acting as an artificial financial market. This computational-experimental approach enabled us to perform several tests, and to validate some hypotheses.

The microstructure of the market model is composed of four kinds of traders (Raberto et al.; 2003):

- Random traders, who trade at random;
- Fundamentalists, who pursue the "fundamental" value;

- Chartists, who are trend-followers and are divided into:
  - Momentum traders, who follow the market trend;
  - Contrarian traders, who follow the opposite of the market trend.

Each trader is modeled as an autonomous agent, with a limited stock portfolio and cash. No trader can issue orders exceeding the finiteness of the resources available to him. The pricing mechanism of each asset is based on the intersection of the demand-supply curves.

In the case of two stock markets, at each simulation step the trader decides in which market to operate by evaluating an attraction function for both markets, and deciding accordingly.

In particular we studied the dynamics of a single market. When the tax was not applied in a closed market, we obtained the same results as reported in Raberto et al. (2003), with fundamentalist and contrarian traders gaining wealth, at the expense of momentum traders and, to a lesser extent, of random traders. We modeled the levy of a transaction tax as a cash draining on each transaction. These latter findings are the focus point of our paper.

We then examined market dynamics and trader's behavior for two stock markets. First we studied the markets with no tax levied, and then the effects of introducing the tax in one market.

We are neither advocates nor detractors of the Tobin tax, but as researchers we look upon the tax simply as a specific measure proposed to achieve a particular economic objective. Our aim is consequently to study whether the introduction of the Tobin tax can stabilize financial markets or not. Levying the tax on one market enabled us to analyze a number of issues, for example whether the taxed market becomes stabler, or volatility in a taxed market is attenuated.

The paper is organized as follows: in Section 2 we present the market model, including trader's behavior, and the price-clearing mechanism. In the subsections of Section 3 we present the results achieved with a single market, and with the interplay of two markets under various tax conditions.

2 Method and Model

In the proposed model, we considered an economy with two stock markets, each trading an asset with similar characteristics, analyzing prices dynamics and traders' behavior.

The model includes both structural and behavioral assumptions. By structural assumptions we intend those trading mechanisms which define the market rules, while behavioral assumptions refer to trading strategies and the rules used by traders for making their decisions (see LiCalzi and Pellizzari; 2002). Each trader is modeled as an autonomous agent, and each is endowed with a given amount of cash and assets. The simulator [1] enables to track the traders' portfolio, the price series history and the orders issued by each trader for each time step. A time step is conventionally one day in duration.

First we examined the dynamics of a single market, both without and with a transaction tax of 0.05% to 0.5%. Then we considered the case of two markets, examining market trend without tax, and then the effects of introducing the tax first in one market, and lastly in both markets.

At each time step, corresponding roughly to one trading day, each trader trades only within one market. Before trading takes place, each trader, in accordance with an attraction function based on expected gain, may decide to leave one market, switching to the other.

The trader model defines the basic behavioral rules for each kind of trader. Each kind of trader is tuned setting the values of some parameters, in such a way that the resulting price series show the well-known "styilized facts", and the price volatility is similar to that found in real markets. Each kind of trader is provided of an "activity" parameter that roughly controls the activity of the trader, and her/his reactivity to the markets, thus influencing the trader's contribution to price volatility. After many trials, we were able to introduce a parameter k common to all kinds of traders – an increase in k leads to an increase in volatility and in volumes.

We concentrated our study on the effects of different distributions of behaviors of the populations of traders on taxed (and non taxed) markets. The price clearing mechanism we used is the same in all simulations, and is "neutral" under this respect. Other works analyzed market dynamics using different market mechanisms and different behavioral rules of traders in terms of stylized facts and of allocative efficiency (see, e.g. Bottazzi et al.; 2005).

We studied the case of a single market, to assess the impact of a transaction tax on price volatility and traders' wealth. Then, we studied two related stock

[1] Our market simulation software has been developed using the GASM (Genoa Artificial Stock Market) (see Raberto et al.; 2001) core. 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.
The model follows an object-oriented approach, and has been implemented in Smalltalk language, following XP (Extreme Programming) software development practices (Beck and Andres; 2004).

markets, to assess the impact of levying a tax on one of them, and on both.

2.1 Traders' behavior

The proposed model includes N traders having four different behaviors: random, fundamentalist, momentum and contrarian. At each simulation step, a trader can issue orders with a given probability, which we usually set at 10% for every trader. In the case of two markets, each trader chooses the most profitable market, according to her/his attraction function.

2.1.1 Random traders

Random traders (type R) are characterized by the simplest trading strategy. They are traders with zero intelligence, and 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 order with equal probability. The order amount is computed at random, but cannot exceed the trader's actual cash and stock availability. The limit price (l_i^b) of a buy order is computed multiplying the current price by a random number drawn from a Gaussian distribution $N(\mu, s_i)$, as shown in equation 1a.

$$l_i^b = p(t) \cdot N(\mu, s_i) \tag{1a}$$

$$l_i^s = p(t)/N(\mu, s_i) \tag{1b}$$

The mean μ is set at a value equal to 1.01 in order to have a spread between the limit prices of sell/buy orders (Raberto et al.; 2003). The standard deviation of this distribution, s_i depends on the historical market standard deviation, $\sigma_i(\tau_i)$, computed on a past price series whose length (τ_i) depends on each trader, according to equation 2:

$$s_i = k * \sigma_i(\tau_i) \tag{2}$$

The limit price (l_i^s) of a sell order is computed fairly symmetrically as shown in equation 1b.

We set the window length τ_i used for random traders to a value randomly chosen for each trader between 2 and 5, while the value of k was set at 1.9. These values are fairly different from those typically used in past simulation with the same model Raberto et al. (2001), that had a longer time window

(3-20), and a lower value of k (about 1.1). In this way, we increased the feedback of price volatility on trader's behavior. In this way, we obtained more realistic price statistical behavior in term of stylized facts, varying the trader population and levying various tax percentages.

2.1.2 Fundamentalist traders

Fundamentalists (type F) 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 last price $p(t-1)$ is lower (higher) than the fundamental price p_f. Fundamentalists' order limits are set toward p_f, and their size (in stocks for sell orders and in cash for buy orders) equals a fraction of the current amount of stocks or cash owned by the trader. This size is proportional to a term q shown in equation 3, where k is the same k used for random traders in equation 2.

$$q = k \cdot \frac{|p(t) - p_f|}{p_f} \tag{3}$$

When a transaction tax is levied, these computations are performed increasing (or decreasing) the current price of the tax value.

2.1.3 Momentum traders

Momentum traders (type M) 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 2 to 10 days.

If the momentum trader issues a buy (sell) order, the limit price l_i is set at the stock's price at the previous time step plus (minus) an increment proportional to the price difference computed in the time window τ_i, as shown in equation 4. The expected increment (or decrement) of the price is divided by the window length, and then multiplied by the same k used for random traders in equation 2. In this way, the trend is always computed proportionally to an estimate of the derivative of prices.

$$l_i = p(t) \cdot \left[1 + k \cdot \frac{p(t) - p(t-\tau)}{\tau p(t-\tau)}\right] \tag{4}$$

If a transaction tax is levied, the current price $p(t-1)$ is adjusted adding (or subtracting) the tax to (from) it, to account for the tax effect.

If a momentum trader decides to sell the quantity of assets that s/he can sell q_i^s cannot exceed the amount of assets $a_i(t)$ owned by the trader i. If a momentum trader decides to buy, the maximum purchasable quantity q_i^b is limited by the cash $c_i(t)$. Both q_i^s and q_i^b are computed proportionally to the absolute value of an estimate of the derivative of prices, as shown in equations 5 and 6

$$q_i^s = a_i(t) \cdot U(0,1) \cdot \left[1 + k \cdot \frac{|p(t) - p(t-\tau)|}{\tau p(t-\tau)}\right] \tag{5}$$

$$q_i^b = \frac{c_i(t)}{p_i(t)} \cdot U(0,1) \cdot \left[1 + k \cdot \frac{|p(t) - p(t-\tau)|}{\tau p(t-\tau)}\right] \tag{6}$$

where $U(0,1)$ is a random draw from an Uniform Distribution between 0 and 1.

2.1.4 Contrarian traders

Contrarian traders (type C) 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. The contrarian trader's order limit price is computed in the same fashion as the momentum traders, but in the opposite direction. The transaction tax is dealt in the same way as for momentum traders.

2.2 Price clearing mechanism

The price clearing mechanism of each market is based on the intersection of the demand-supply curve. At each simulation step, the traders issue their buy or sell orders with their limit prices, computed as described in section 2.1. We adopted the algorithm described in Raberto et al. (2001), where price clearing is obtained by the intersection of supply and demand curves.

Let (a^b_u, b_u), $u = 1, ..., U$, be the data associated to the U buy orders. In each pair, the quantity of stock to buy, a^b_u, is associated with its limit price, b_u. As regards the V selling orders, they are represented by pairs: (a^s_v, s_v), $v = 1, ..., V$. Here the quantity to sell is a^s_v, while its associated limit price is s_v. The cleared price, p^*, is determined by intersecting the two functions:

$$f_{t+1}(p) = \sum_{u|b_u \geq p} a^b_u \qquad (\textit{Demand curve}) \tag{7}$$

$$g_{t+1}(p) = \sum_{v|s_v \leq p} a^s_v \qquad (\textit{Supply curve}) \tag{8}$$

The orders matching the new price p^*, i.e. buy orders with maximum price lower than or equal to p^*, and selling orders with minimum price higher than or equal to p^*, are executed. Subsequently, the amount of cash and assets owned by each trader are updated.

2.3 Attraction functions

In the case study of two markets, at each simulation step (t), the trader decides in which market s/he prefers to trade by evaluating an attraction function for both markets. Let $A^{T,i}_1(t)$ and $A^{T,i}_2(t)$ be the attraction functions for the i-th generic trader of type T for the first and second market, respectively. At each step, the i-th trader chooses the first market with probability $\pi^i_1(t) = \frac{A^{T,i}_1(t)}{A^{T,i}_1(t)+A^{T,i}_2(t)}$, and the second one with probability $\pi^i_2(t) = 1 - \pi^i_1(t)$.

In most simulations, the trader populations of two markets do not differ significantly – no more than a few percentage points. However, in about 1-2% cases, it may happen that one market becomes too attractive compared to the other, triggering an avalanche of traders and leaving empty – or almost empty – the other market. To avoid this divergent behavior, we constrained the values of the probability function $\pi^i_1(t)$ to a minimum set at 0.3. This value is somewhat arbitrary, but it is enough to completely avoid the problem, without introducing any significant side-effect in the simulations.

As regards attraction functions, they have been designed taking into account the specific characteristics of various kinds of traders.

Random traders represent the bulk of traders operating in the market for personal reasons, or with no specific trading strategy. When faced with the possibility to operate in one of two markets, they naturally tend to prefer the less volatile one. Moreover, they also tend to avoid the market with higher tax rate. In our model, at each simulation step random traders choose randomly to buy or sell, with equal probability. If a random trader decides to sell, her/his attraction function reflects the considerations made above, and is shown in equation 9.

$$A^{R,i}_{j,sell} = e^{\sigma_j^2(\tau_i)}(1 - tax_j) \tag{9}$$

The superscript R denotes the random trader, j denotes the j-th asset, and $\sigma_j^2(\tau_i)$ represents the volatility of the returns computed in the time window τ_i specific for each trader. The exponential term ensures that random traders prefer to sell in a volatile market. The $(1 - tax_j)$ term reduces the attraction of a taxed market, being tax_j the transaction tax imposed in $j - th$ market. For instance, if the tax is 1% in market j, the term tax_j is set at 0.01.

If a random trader decides to buy, s/he performs this action in a less volatile market with an higher probability. So, the probability that a random trader buys in a less volatile market equals to the probability that a random trader sells in a more volatile one. The attraction function is given by equation 10.

$$A^{R,i}_{j,buy} = e^{-\sigma_j^2(\tau_i)}(1 - tax_j) \tag{10}$$

Fundamental analysis requires a deep knowledge of the market. Fundamentalists thus tend to concentrate on a limited number of markets (Westerhoff; 2004). In our model, each fundamentalist issues orders in one market only, where s/he is more knowledgeable, so for each of them the attraction function of one market is one, and that of the other market is zero. The fundamentalist traders' population is equally divided between the two markets, as well as their total initial wealth.

Momentum and contrarian traders are trend-followers, so they choose the market depending on the trend of past prices. Basically they prefer the market with the highest trend, computed in their time window τ_i. They also take into account the transaction tax rate, in the same way of random traders. These choices are reflected in the attraction function reported in 11.

$$A^{M,i}_j = A^{C,i}_j = e^{\frac{|p_j(t) - p_j(t-\tau_i)|}{\tau_i p_j(t-\tau_i)}}(1 - tax_j) \tag{11}$$

3 Results

In this section we describe the results of the computational experiments we performed.

We studied the effectiveness of the Tobin tax in two steps. In section 3.1 we discuss one market only, first without the tax, then levying a tax rate between 0.05% and 0.5% on each transaction.

In section 3.2 we discuss two markets, first with no tax applied, and then applying the tax to the first.

We performed several simulations for all cases. Each simulation is usually run with 4,000 time steps (corresponding to a time span of 20 years), and with 400 agents, each with a probability $p = 0.1$ to trade at each time step. We also performed some simulation runs with 4000 agents, each with a probability $p = 0.01$ to trade at each time step. In this way, the average number of market transactions is the same of the previous case, but each traders trades places on average ten times less transactions, thus maintaining virtually unchanged his/her wealth, irrespectively of the trading strategy and of the tax.

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. On the other hand, in the real world market traders' wealth is unequally distributed. In the case of one market, each trader is endowed with an average \$50000 cash (\$70000 for two markets) and in both cases with an average 1000 stocks (per market).

At the beginning of the simulation, the starting price of the asset, and the fundamental price used by fundamentalists, is set at a value equal to the total wealth divided by the number of assets and multiplied by the square root of the number of markets. This value has been found to be the "equilibrium" value for markets with only random traders.

For each trader configuration we performed 20 runs. In some cases, we also performed 50 runs, but we never found results significantly differing from those obtained with 20 runs.

3.1 One market

As described in 3.1.1 and 3.1.2 we first tested the overall behavior of our model, varying the percentage of fundamentalists from zero to 30%, in steps of 10, and the percentage of chartists from zero to 30% in a similar fashion. Note that chartists always comprise the same percentage of momentum and contrarian traders. Then we tested our model keeping the percentage of fundamentalists (20%) and of chartist (20%) unchanged but varying the percentage of momentum versus contrarian traders in 5% steps.

3.1.1 One market with no transaction tax

When the tax is not levied in a closed market, we obtained results similar to those reported in Raberto et al. (2003), with fundamentalists and contrarian traders gaining wealth with time, at the expense of momentum traders and, to a lesser extent, of random traders. Price series show the usual "styilized facts", with fat tails of returns and volatility clustering. For the sake of brevity, these results are not reported here. Note that, as discussed in section 2.1, the trader models are not the same of previous reported simulations Raberto et al. (2003), but now all depend on the same coefficient k, able to control trader's reaction to price trend, and thus to tune market volatility. After many test runs, we set the value of k at 1.9, which guarantees the appearance of the price series stylized facts for virtually every trader composition used. As regards price variance, with the new method it exhibits values higher than that of real markets, yielding price variations two or three times higher. However, we believe that this feature could be useful to better ascertain the effect of the tax on volatile markets.

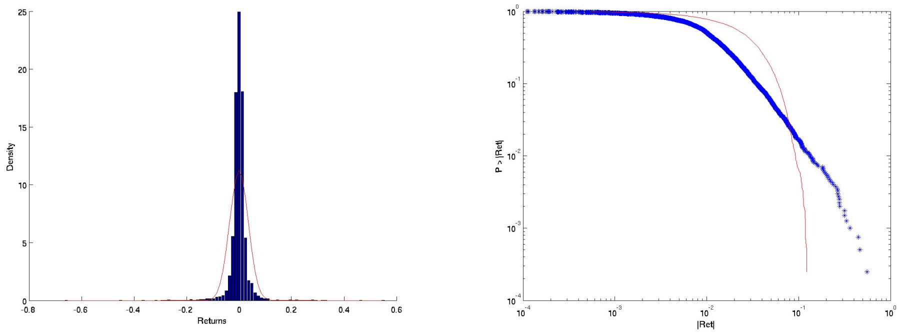
In Fig. 1(a) we plot the histogram of daily log-returns: a best-fit normal distribution is superimposed; its narrow peak is well defined and typical of all simulations we ran with model 2 traders. Fig. 1(b) shows the survival probability distribution of the standardized logarithmic return. The solid line represents the survival probability distribution of the best fit and the bold stars represents the survival probability distribution of the returns. The deviation from Gaussian distribution shows again a leptokurtotic behavior in the returns tail, with a very well defined power-law behavior for high values of returns.

Here we describe the results of several simulations performed varying the percentage of fundamental and chartist traders from 0% to 30% in steps of 10%, the rest of traders being random.

Table 1 shows the average and the standard error of price volatility, computed for the case of no Tobin tax.

Volatility of the returns was computed as the variance during period T:

$$\sigma_r^2 = \frac{1}{T-1}\sum_{t=1}^{T}(r_t - \bar{r})^2 \tag{12}$$



(a) Histogram (b) Survival

Fig. 1. *Histogram of the distribution of daily log-returns superimposed on the best normal fit (left) and survival probability distribution (right).*

where $r_t = ln(p(t)) - ln(p(t-1))$ represents the logarithmic returns at the instant t. We always omitted to include in price volatility computation the first 250 simulation steps, to accommodate possible initial transient effects on price volatility.

As regards the width of time window T, we performed various tests, varying T between 5 and 50 time steps. In all cases, irrespectively of trader composition and tax value, we found very stable average price variance values, slowly decreasing with T. The percentage difference of average price volatility between the case $T = 5$ and the case $T = 50$ is always below 12%. We then decided to use the value $T = 10$, which guarantees the best trade-off between low and high values of the time window used to compute price volatility.

Table 1
Mean and Standard Error of volatility in a single market with no tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**10%**	**20%**	**30%**
0%	1.61 (0.21)	0.78 (0.1)	0.46 (0.07)	0.19 (0.01)
10%	4.33 (0.44)	1.42 (0.16)	0.49 (0.03)	0.22 (0.01)
20%	7.31 (0.62)	2.41 (0.31)	0.6 (0.06)	0.27 (0.04)
30%	15.17 (0.99)	2.94 (0.33)	1 (0.1)	0.26 (0.02)

The results of the simulations are reported in Table 1. In these runs, price volatility decreases as the percentage of chartists increases, and increases as the percentage of fundamentalists decreases. These results are fairly robust and repeatable, because the presented figures are an average over 20 runs each, and their standard error is usually quite lower than volatility itself. Since they are not obvious, we will discuss them in detail.

In the presented model, random traders alone are able to produce a consistent volatility of prices, for two main reasons:

- their wealth is distributed according to a Zipf's law, so from time to time large orders are posted by the richest traders, able to produce significant price variations;
- the limit price of orders is randomly chosen, according to a Gaussian distribution with variance depending on past price volatility; this introduces a GARCH-like effect, able to yield volatility clustering and to increase overall price volatility.

On the other hand, chartists are equally composed of both momentum and contrarian traders. While momentum traders can destabilize the market, and thus increase its volatility, contrarian traders tend to stabilize it, and basically counteract the effect of momentum traders. The conjunct behavior of both population tend to stabilize the market, with respect to the effect of random traders, whose number decreases as the total number of chartists increases.

As regards fundamentalists, price volatility sharply increases as the percentage of fundamentalists increases. This phenomenon is related with the prompt intervention of fundamentalists when prices diverge from the fundamental value. In practice, occasional big price variations due to large orders posted by random traders, with a limit price quite different form the current price, are immediately counter-acted by fundamentalists, with a strength proportional to the original variation. This behavior drives prices toward the fundamental value, thus adding volatility to the system. Indeed, fundamentalists can be seen as "short memory" traders, since they look only at the last realized price. The destabilizing behavior of "short memory" traders is in line with what found in other agent-based investigations.

In Fig. 2 we report the dynamics of wealth of the four populations of traders for a simulation of 2000 steps. Here both fundamentalists and chartists are at 10% of total trader population. Fundamentalists and contrarian traders tend to increase their wealth at the expense of momentum traders and, to a lesser extent, of random traders, confirming again the results reported in Raberto et al. (2003) The decreasing wealth of momentum traders, however, does not substantially affects their behavior and their effect on the price.

3.1.2 One market with transaction tax

Here we show the effects of the tax on a single market. We performed many runs, varying the percentages of the trader populations and the tax rate. The tax rate is set at 0.1% and 0.5%. The former figure is within the range usually

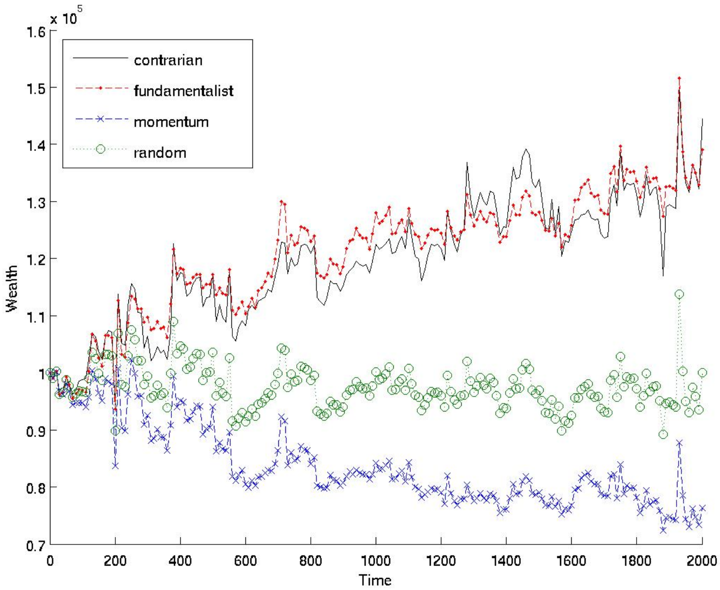


Fig. 2. *Dynamics of wealth of the four populations of traders for a simulation of 2000 steps.*

proposed and discussed by supporters and detractors of a transaction tax, while the latter figure is much higher, and is used to analyise the effects of an amplified tax. Note that, since both buyer and seller pay the tax, all these figures should be doubled.

Introducing the tax in one market enabled to analyze a number of issues, which are debated among its supporters and detractors. Namely, if the taxed market becomes stabler or not, and how volatility and trading volumes change. In all reported cases, the simulations show the stylized facts of price series (return autocorrelation, fat tails, volatility clustering).

The results report the price volatility, and its standard error, averaged over 20 runs each. The simulations were performed using 400 traders and 2000 time steps, varying the percentages of the trader populations as in the previous section.

Since our market model has finite resources, levying a tax leads to a reduction of total traders' wealth with time, that may be significant for the highest tax rates. To compensate for this effect, we computed the cash outflow due to the tax every 100 steps, and endowed traders chosen at random with small cash amounts whose total equals the cash outflow.

Table 2 shows average and standard error of price volatility, computed for a Tobin tax of 0.1%.

In this case, for low (10%) or zero chartist percentage, there are no remark-

Table 2

Mean and Standard Error of volatility in a single market with 0.1% tax. The results are multiplied by 10^3.

Fundamentalist	***Chartist*** 0%	10%	20%	30%
0	1.62 (0.14)	0.7 (0.04)	0.45 (0.04)	0.28 (0.03)
10%	3.71 (0.33)	1.35 (0.14)	0.6 (0.07)	0.31 (0.01)
20%	7.78 (0.79)	2.44 (0.25)	0.74 (0.08)	0.36 (0.03)
30%	14.44 (1.35)	2.99 (0.28)	1.32 (0.16)	0.56 (0.04)

able differences with the no tax market. As the chartist percentage increases, however, volatility increases substantially except when no fundamentalists are included. This increase may be as much as 80%, for the greatest percentage of fundamentalist and chartist traders. Table 3 shows average and standard error of price volatility, computed for a Tobin tax of 0.5%.

Table 3

Mean and Standard Error of volatility in a single market with 0.5% tax. The results are multiplied by 10^3.

Fundamentalist	***Chartist*** 0%	10%	20%	30%
0	1.06 (0.16)	0.85 (0.09)	0.66 (0.03)	0.71 (0.04)
10%	3.06 (0.41)	1.36 (0.12)	1.15 (0.1)	1.04 (0.09)
20%	5.74 (0.56)	2.73 (0.25)	1.89 (0.15)	1.55 (0.11)
30%	11.05 (0.64)	5.51 (0.28)	3.12 (0.24)	2.25 (0.12)

For markets with random and fundamentalists traders alone, levying the tax produces a small reduction in volatility, which varies with fundamentalist percentage, and can reach 5-8% (tax = 0.1%), and even 30-40% (tax = 0.5%). Increasing the percentage of fundamentalists increases even more the volatility in the presence of the tax.

When chartists are taken into account, the tax systematically leads to an increase in volatility, which can be up to 80% in the case of tax = 0.1%, and up to 7-fold in the case of tax = 0.5%, for the highest percentage of chartists. This effect is evident when chartist percentage is 20% or 30%. When chartists are 10% of the whole trader populations, the increase in volatility is significant only if fundamentalists are at 30% percentage.

To gain more insight into this behavior, we performed several runs with a market model with 10% fundamentalists, 5% momentum traders and 5% contrarian traders, varying the tax from 0 to 1% with steps of 0.025%. Each tax percentage has been simulated 10 times, and the resulting price variances averaged. Figure 3 reports the results. The steady increase in volatility is patent, despite the noise in measurements, and confirms the results reported above.

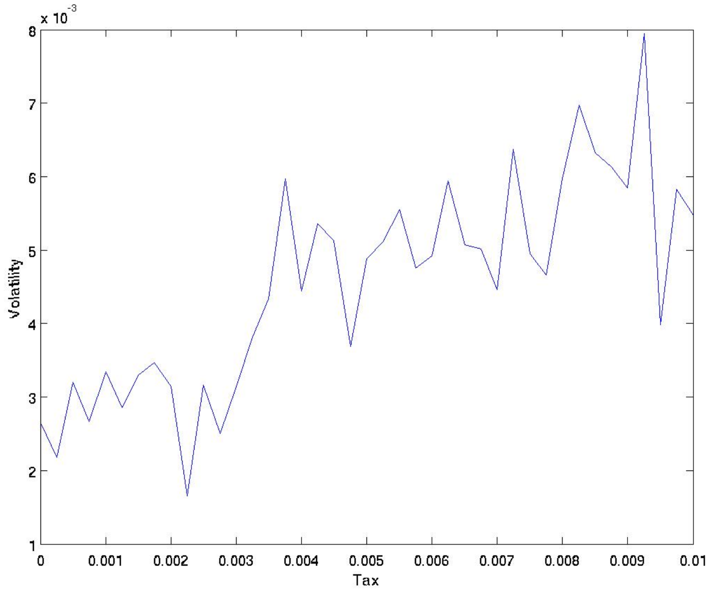


Fig. 3. *Price variance as a function of tax rate in the case of 10% fundamentalist and 10% chartist traders.*

Using this model, there is a steady increase in price volatility as the tax rate increases, provided that there are enough chartists. With no chartist, price volatility tends to slowly decrease as the tax rate increases. These results are in agreement with empirical findings by Umlauf (1993) and by Aliber et al. (2003), who observed a price volatility increase with tax rate (or, better, with transaction costs).

We conducted further tests keeping the percentage of fundamentalists (20%) and of chartists (20%) unchanged, but varying the percentage of momentum versus contrarian traders in 5% steps.

In Table 4, we show the results of these simulations. The volatility increase as a function of the tax rate is confirmed in all cases, but when there is no contrarian trader. With this model, an "extreme" chartist composition, made only of contrarian or momentum traders, seems to increase volatility, while more balanced compositions present a lower volatility. Momentum traders tend to increase volatility more, especially when no tax, or a small tax, is levied.

Fig. 4 shows the daily time series for logarithmic returns of prices for a typical simulation with a trader population composed of 20% fundamentalist, 10% momentum, 10% contrarian, and a 0.05% tax rate. Note that prices always

Table 4
Mean and Standard Error of volatility computed for different contrarian traders percentages, p_c. The total percentage of chartists is always 20%. All values are multiplied by 10^3.

Tax rate %	p_c =20% Mean (stEr)	p_c =15% Mean (stEr)	p_c =10% Mean (stEr)	p_c =5% Mean (stEr)	p_c =0% Mean (stEr)
0.0	1.83 (0.13)	0.62 (0.07)	0.58 (0.06)	1.15 (0.11)	4.88 (0.46)
0.1	1.96 (0.28)	0.95 (0.08)	0.71 (0.07)	1.25 (0.09)	4.31 (0.26)
0.5	4.7 (0.31)	2.26 (0.14)	1.84 (0.14) 2.2 (0.19)	4.78 (0.26)	

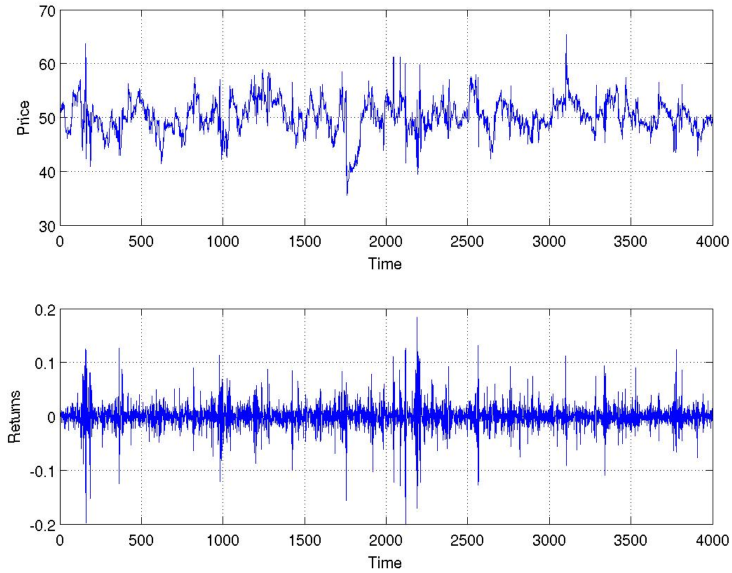


Fig. 4. *Daily time series for prices (top) and returns (bottom).*

oscillate around 50. It is due to the fact that the finite amount of cash and stocks yields mean-reversion on prices around a constant long-run mean which depends on the ratio between the global amount of cash and the global number of shares (Raberto et al.; 2003). We set the fundamental price $p(f)$ of fundamentalist traders equal to 50.

In our model, the increase of volatility could be explained by the reduction of orders when a tax is applied. Note that we have 400 agents, and on average 40 active agents at each time step, resulting in an average of 20 sell orders and 20 buy orders of different sizes. If transaction taxes reduce these numbers, and also the agent's trading amount, the demand and supply curves from which the prize is derived becomes much more fuzzy, amplifying price variations. The relation between transaction taxes, market depth and price volatility is also explored by Ehrenstein et al. Ehrenstein et al. (2005), yielding similar results.

In tables 5, 6 and 7, we report the average daily volumes corresponding to the cases studied. The traded volumes change much less than volatility as trader composition and tax rate change. However, you may note in many cases a strong anti-correlation between volatility and volumes.

Table 5
Daily volumes and standard deviations in a single market with 0.0% tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**10%**	**20%**	**30%**
0%	9.51 (4.09)	10.04 (4.28)	10.63 (4.49)	11.17 (4.75)
10%	8.02 (3.35)	8.69 (3.71)	9.28 (4.02)	9.94 (4.34)
20%	6.92 (2.90)	7.54 (3.32)	8.19 (3.67)	8.76 (3.98)
30%	5.80 (2.52)	6.43 (2.96)	7.12 (3.37)	7.69 (3.70)

Table 6
Daily volumes and standard deviations in a single market with 0.1% tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**10%**	**20%**	**30%**
0%	9.51 (4.05)	9.82 (4.15)	10.07 (4.29)	10.18 (4.41)
10%	8.06 (3.34)	8.41 (3.56)	8.75 (3.80)	8.91 (4.02)
20%	6.85 (2.86)	7.27 (3.17)	7.57 (3.42)	7.70 (3.67)
30%	5.76 (2.48)	6.16 (2.84)	6.44 (3.10)	6.57 (3.32)

Table 7
Daily volumes and standard deviations in a single market with 0.5% tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**10%**	**20%**	**30%**
0%	9.87 (3.96)	9.30 (3.82)	8.82 (3.82)	8.41 (3.92)
10%	8.16 (3.25)	7.78 (3.23)	7.35 (3.27)	7.01 (3.38)
20%	6.88 (2.81)	6.57 (2.86)	6.19 (2.89)	5.88 (3.00)
30%	5.73 (2.45)	5.44 (2.49)	5.15 (2.58)	4.87 (2.72)

Westerhoff, using a different model with unlimited resources found a different behavior – a reduction in volatility for low tax rates, increasing as rates are increased (Westerhoff; 2003). These results confirm how difficult it is to assess, using a theoretical model, the impact of a change in market regulation and suggest continuing these studies, to gain a greater insight into market behavior.

3.2 Two markets

In this subsection we discuss the second part of our experiment. We analyzed two markets first levying no transaction tax and then introducing the tax in one market, leaving the other not taxed. The rules enabling traders to switch from one market to the other has been reported in Section 2.3. We recall that fundamentalists traders do not switch between markets.

Initial cash and stock endowment of traders was chosen with the constraint that wealth is balanced in the two markets. We performed various simulations varying fundamentalist and chartist percentage between 0% and 20%, always keeping balanced momentum and contrarian traders. In this way, we had at the same time a "thermal bath" of random traders, and a large enough number of other types of traders to make their influence emerge in the price dynamics.

The number of traders used in each simulation was 4000, with a probability to trade at each time step of 2%. In this way, we were able to generate for each market the same average number of orders we had in the simulations with a single market. Remember that in single market simulations we had 400 traders, with a probability to trade at each time step of 10%. The much higher number of traders has been chosen in order to minimize possible side-effects due to increase or reduction of wealth in specific trader kinds.

Each configuration was simulated 20 times, using 2000 time steps each, and we computed the average variance (volatility) of prices and the standard error of this variance, to assess price volatility data consistency. The variance has been computed for intervals of 10 time steps, discarding the first 250 steps, as in previous runs.

3.2.1 Two markets: no transaction tax

Here we examine the dynamics of two markets with no transaction tax. When no tax is levied in neither of the closed markets, we obtain the classical stylized facts (returns autocorrelation, fat tails, volatility clustering), which we found in the case of a single market. For the sake of brevity, we do not report these results here.

Tables 8 and 9 report the average and the standard error of price volatility, computed for the case of no Tobin tax, varying fundamentalists and chartists percentages.

Price volatility values confirm that both markets behave in the same way. Moreover, in this case the number of traders moving from one market to another, and vice-versa, are balanced in both markets. Volatilities are fairly higher than in corresponding Table 1, denoting that the presence of two markets, with switching of traders between them, tends to increase price volatility. Also in this case, price volatility decreases as the percentage of chartists increases, and increases as the percentage of fundamentalists increases.

Table 8

Mean and Standard Error of volatility in market one. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**5%**	**10%**	**20%**
0%	5.62 (0.58)	3.72 (0.5)	2.04 (0.25)	0.67 (0.08)
5%	8.15 (1.34)	4.2 (0.61)	1.89 (0.28)	0.79 (0.15)
10%	12.18 (1.87)	4.88 (0.79)	3.92 (0.71)	1.07 (0.19)
20%	37.22 (3.42)	19.38 (2.15)	7.49 (0.88)	2.25 (0.36)

Table 9

Mean and Standard Error of volatility in market two. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**5%**	**10%**	**20%**
0%	4.9 (0.73)	3.87 (0.84)	1.95 (0.27)	0.67 (0.09)
5%	8.12 (1.53)	4.07 (0.66)	1.88 (0.29)	0.74 (0.09)
10%	7.99 (1.14)	5.08 (0.76)	2.26 (0.27)	1.01 (0.18)
20%	35.65 (3.22)	17.23 (1.87)	7.78 (1.02)	2.04 (0.48)

In Fig. 5 we report the dynamics of wealth of the four populations of traders in both markets, for a simulation of 2000 steps. Both fundamentalists and chartists are at 10% of total trader population. Also in the case of two markets, fundamentalists and contrarian traders tend to increase their wealth at the expense of momentum traders and random traders. The reported wealth differences are less pronounced than in the case of one market, but you should remember that in this case traders are 4000, and tend to trade five times less than in the case of a single market.

3.2.2 Two markets: transaction tax in one of them

Here we discuss two markets, levying the tax in just one of them (Market 1). When levying a tax on Market 1 transactions, we obviously observed total

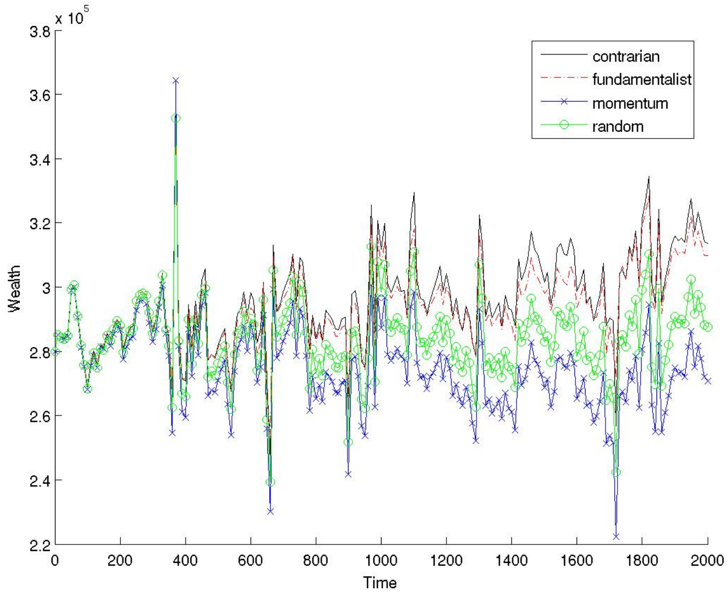


Fig. 5. *Dynamics of wealth of the four populations of traders for a simulation of 2000 steps, in the case of two markets.*

traders' wealth decreasing over time, because our market model has limited resources. This decrease affects both cash – because the tax is exacted in cash – and prices – because a cash shortage impacts prices. If the fundamental price (p_f) is not adjusted accordingly to cash decrease, in a closed market after a while fundamentalists also lose wealth, because they tend to push prices towards their fundamental value which becomes unsustainable. They buy all the stocks they can and then stay still, while the value of their stocks slowly decreases. However, in our simulations the cash drain due to the tax is negligible, because the tax rate is low, the number of transaction made by each trader is low as well, and the number of simulated time steps is limited. Thus, the reported results are not affected by the cash leakage due to the tax.

Tables 10 and 11 report the average and the standard error of price volatility, computed for the case of tax rate 0.1%, varying fundamentalists and chartists percentages. Tables 12 and 13 report the same configurations and data, this time computed for a tax rate 0.5%.

These experiments confirm some findings made in a single market, and in two markets with no tax. The first observation is that having two markets leads to a strong increase in price volatility. This phenomenon might be explained with the unbalance of cash and stocks with respect to one market. However, we performed some simulations with one market, varying initial cash endowment of traders, leaving unchanged their stock endowment, and did not find any change in volatility. Note that volatility increases 3-4 times even in the case of markets with only random traders, who switch between the markets trying to reduce their risk. They tend to sell in the more volatile market, and to buy in

Table 10
Mean and Standard Error of volatility in market one, with 0.1% transaction tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**5%**	**10%**	**20%**
0%	7.27 (0.99)	3.88 (0.59)	2.96 (0.48)	1.16 (0.17)
5%	5.88 (0.76)	4.38 (0.53)	2.23 (0.44)	1.36 (0.26)
10%	11.55 (1.26)	7.16 (1.02)	3.39 (0.52)	1.28 (0.17)
20%	43.12 (4.44)	16.71 (1.87)	10.86 (1.3)	2.71 (0.52)

Table 11
Mean and Standard Error of volatility in market two, with 0.1% transaction tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**5%**	**10%**	**20%**
0%	6.16 (0.81)	3.19 (0.47)	2.45 (0.43)	0.85 (0.08)
5%	5.77 (0.69)	3.89 (0.67)	2.8 (0.38)	0.68 (0.09)
10%	11.48 (1.83)	7.44 (1.05)	2.1 (0.31)	1.33 (0.24)
20%	36.92 (4.61)	17.62 (2.29)	7.05 (1.05)	1.56 (0.19)

Table 12
Mean and Standard Error of volatility in market one, with 0.5% transaction tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**5%**	**10%**	**20%**
0%	6.76 (0.92)	5.06 (0.65)	3.14 (0.44)	2.05 (0.26)
5%	5.28 (0.67)	4.82 (0.93)	3.95 (0.73)	2.24 (0.28)
10%	11.09 (1.57)	6.61 (0.83)	5.77 (0.88)	3.81 (0.66)
20%	36.1 (3.64)	29.09 (2.48)	16.26 (1.69)	7.28 (0.72)

the less volatile one, as reported in equations 9 and 10 (section 2.3). Probably, this behavior creates an imbalance in orders which yields an overall volatility increase. The intrinsic mean reversion mechanism due to limited traders resources avoids long-term imbalance between the two markets. The presence of fundamentalists seems to lower this increase in volatility, while the presence of high percentages of chartists and fundamentalists together amplifies it – in the case of 20% fundamentalists and 20% chartists, we observed a 8-9 fold

Table 13
Mean and Standard Error of volatility in market two, with 0.5% transaction tax. The results are multiplied by 10^3.

	Chartist			
Fundamentalist	**0%**	**5%**	**10%**	**20%**
0%	5.58 (0.61)	4.54 (0.79)	1.98 (0.29)	0.89 (0.15)
5%	6.98 (1.11)	3.52 (0.7)	1.91 (0.35)	0.72 (0.1)
10%	12.09 (1.84)	3.74 (0.6)	4.05 (0.74)	1.02 (0.24)
20%	43.63 (3.79)	18.06 (2.1)	5.92 (0.86)	1.1 (0.12)

increase (see Tables 1, 8 and 9).

We also note that the effects of the tax observed in a single market (substantial indifference in the case of random and fundamentalist traders alone, volatility increase in the presence of chartists) are totally confirmed in the case of a tax levied on one market, linked to a second one with no tax. The volatility increase is however less pronounced, maybe because the market volatility is already very high.

The most remarkable effect we found, however, is the fact that the taxed market presents a higher volatility with respect to the linked untaxed market, in all cases when the tax has significant effects, that is in the presence of chartists. When the market is very speculative, i.e. for the highest percentages of chartists, the untaxed market reports a volatility decrement with respect to the case of no tax, while the taxed market shows a strong volatility increment, thus somewhat "adsorbing" further volatility from the former.

Table 14 reports the average daily trading volumes in both markets, for various trader compositions and tax rates. The taxed market is, as always, Market 1. The reported values are averaged on 20 simulations each, and standard errors are also reported.

In the case of no tax, there is no significant difference in average volumes between the markets, as expected. The presence of the tax leads to smaller volumes in the taxed market with respect to the other, in all cases when the tax introduction yields a price volatility increase in the taxed market. The difference in trading volumes is not as remarkable as the difference in volatility, and is at most of the order of 20%. This finding confirms, however, that traders tend to escape from the taxed market, and that a lower volume triggers an increase in volatility, as discussed in Section 3.1.2.

Table 14
Daily average volumes. If there is a tax, it is levied only on market one. The results are divided by 10^3

Population		*No Tax*		*0.1% Tax*		*0.5% Tax*	
F.	**C.**	**Mkt1**	**Mkt2**	**Mkt1**	**Mkt2**	**Mkt1**	**Mkt2**
0%	0%	9.49 (4.71)	9.48 (4.66)	9.55 (4.79)	9.46 (4.71)	9.47 (4.77)	9.57 (4.79)
0%	10%	9.97 (4.70)	10.01 (4.71)	9.81 (4.65)	9.91 (4.69)	9.37 (4.57)	9.85 (4.65)
0%	20%	10.55 (4.80)	10.63 (4.84)	10.13 (4.72)	10.54 (4.82)	9.26 (4.60)	10.31 (4.72)
10%	0%	8.61 (4.20)	8.60 (4.20)	8.56 (4.19)	8.61 (4.19)	8.57 (4.22)	8.68 (4.22)
10%	10%	9.24 (4.41)	9.29 (4.40)	9.05 (4.36)	9.25 (4.44)	8.51 (4.20)	9.25 (4.41)
10%	20%	10.01 (4.71)	9.95 (4.73)	9.44 (4.52)	9.99 (4.70)	8.40 (4.28)	9.96 (4.67)
20%	0%	7.91 (4.02)	7.87 (4.01)	7.85 (4.02)	7.89 (4.00)	7.82 (3.96)	7.91 (4.02)
20%	10%	8.50 (4.22)	8.47 (4.24)	8.30 (4.16)	8.50 (4.20)	7.78 (3.95)	8.58 (4.24)
20%	20%	9.17 (4.47)	9.12 (4.44)	8.76 (4.37)	9.21 (4.51)	7.77 (4.10)	9.27 (4.50)

4 Conclusions

In this paper we presented a study on the impact of securities transaction taxes in financial markets, performed using an artificial stock market. We used a simple market model with four kinds of agents, modeling typical traders' behavior in financial markets: random traders, fundamentalists and two kinds of chartists. The market model is closed, as each trader is endowed with a limited amount of cash and stocks. The price clearing mechanism matches supply and demand curves. The market parameters are tuned in such a way that a simulation step roughly corresponds to a trading day. Overall, this market model is fairly complete, and yields price series with the classical stylized properties found in real price series, i.e. apparent random-walk behavior of prices, fat-tailed distribution of returns and volatility clustering.

At first we performed many computations with a single market, varying trader composition and tax rate. Levying a tax significantly influences market behavior, even with small tax rates. The price volatility consistently increases with the tax rate, but only when chartist traders are present in the market.

These results are in agreement with many empirical findings, and assess, using a theoretical model, the impact of a change in market regulation. However, they cannot deemed in any way to be conclusive. Slightly different trader and/or market models can yield very different results. So, further studies are needed to gain a greater insight into market behavior.

We studied then two related markets, giving each trader the chance to choose at each time step the market s/he prefers to trade in, according to an attraction function. We performed simulations on this market pair with no tax levied, and taxing one market. The first finding is that, irrespective of the trader composition and the tax rate, the interplay of markets leads to a fairly higher price volatility.

The second finding indicated that, despite the small transaction tax (typically 0.1-0.5% of transaction cost) and the simple trader models used, the tax does heavily impact on market behavior, increasing price volatility and decreasing trading volumes. This happens only with traders compositions sensitive to the tax, namely those including chartist traders. Despite the low tax rate, introducing the transaction tax significantly increases prices volatility, computed for different time horizons, and decreases volumes, thought to a lesser extent.

These findings confirm the view that an increase in transaction costs produced by levying the tax, leads to a reduction in market volume and to greater volatility. This behavior appears quite robust, in the sense that the effects of the tax are experienced for most trader compositions, and do not depend on the interplay between two markets, but are encountered even in a single market. The only condition to find this behavior is having in the market speculative traders who follow the trend of prices (or the anti-trend). In fact, the tax does not seem to influence significantly markets composed only of random and fundamentalist traders.

These findings seem to contradict the results reported by Westerhoff and Dieci (2004 in press), who found in their model that when a transaction tax is imposed in one market, speculators leave this market which becomes less volatile. However, this contradiction is only apparent. Westerhoff and Dieci's model is much more sophisticated than ours in accounting for the switching between markets by informed speculators, while in our model the attractivity function is operated by near zero intelligence traders. In our work, we found essentially that, in a realistic yet simple market model, levying a transaction tax yields a reduction in trading volume and an increase in volatility. A more sophisticated model, accounting more carefully for risk aversion, and for the fact that speculators actually leave the taxed market, could substantially modify the composition of traders in the markets, yielding different results.

5 Acknowledgements

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