

The use of agent-based financial market models to test the effectiveness of regulatory policies*

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Abstract

Models with heterogeneous interacting agents have proven to be quite successful in the past. For instance, such models are able to mimic the dynamics of financial markets quite well. The goal of our paper is to explore whether this approach may offer new insights into the working of certain regulatory policies such as transaction taxes, central bank interventions and trading halts. Although this strand of research is rather novel, we argue that agent-based models may be used as artificial laboratories to improve our understanding of how regulatory policy tools function.

Keywords

Financial markets; technical and fundamental analysis; transaction taxes; central bank intervention; trading halts.

JEL classification

G15; G18.

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1 Introduction

Financial markets repeatedly display spectacular bubbles and crashes. Well-known examples include the evolution of the prices for gold and silver in the early 1980s, the development of the DEM/USD exchange rate in the mid 1980s, the course of the Japanese stock market between 1985 and 1995, the world-wide collapse of the stock markets following the year 2000 and the turbulent swings of the euro since its launch in 1999. In addition, the volatility of financial markets is quite high. For instance, the DEM/USD exchange rate changed by about 0.5 percent every day between 1974 and 1998. Commodity and stock prices can be even more volatile. The price of crude oil varied on average by about 1.7 percent every day between 1986 and 2000 (see Shiller 2000 and Sornette 2003 for lively overviews). As a result, policy makers are periodically tempted to regulate financial markets using diverse mechanisms such as transaction taxes, central bank interventions and trading halts. However, it is not entirely clear how these tools may affect the dynamics of financial markets. Our goal is to address this important issue from an agent-based financial market perspective.

According to Axelrod and Tesfatsion (2006), agent-based modeling is a method used to study systems (a) which are composed of interacting agents and (b) which exhibit emergent properties, i.e. properties arising from the interactions of agents, which cannot be deduced simply by aggregating the agents' properties. Obviously, this approach is well suited for modeling many social and economic phenomena. Neither are all human beings alike nor may we truly understand features such as social norms, civil violence, residential segregation or fads and herding behavior by inspecting the action of an isolated representative agent. The collective volume of Tesfatsion and Judd (2006) contains a number of interesting social and economic applications of this theme.

Agent-based models used in finance have recently been reviewed by Hommes (2006) and LeBaron (2006). While LeBaron concentrates more strongly on large type models with hundreds of heterogeneous traders who may apply an evolving set of rather sophisticated trading strategies, Hommes focuses on small type models with only a few different types of traders. Without question, both approaches have their merits. Here, we follow the route of Hommes, restricting ourselves to fairly simple models. One advantage of this is that we are able to pin down some of the causalities acting inside these models. Our plan is to illustrate potential consequences of regulatory policies with the help of a specific agent-based model and to sketch some findings of related papers to illustrate what kind of new arguments we may obtain from such a research direction.

For this reason, we develop a simple model in which market participants may use technical or fundamental trading strategies to determine their orders or they may abstain from the market. The decision in favor of one of these three strategies is repeated every trading period and is based on the strategies' past performance. For instance, should the agents observe that fundamental analysis was unprofitable in the last trading periods, then at least some of them will stop using this strategy. As we will see in more detail later, such an agent-based financial market model may help us to comprehend the dynamics of financial markets. For instance, it reveals that nonlinear interactions between heterogeneous market participants may account for emergent phenomena such as bubbles and crashes, excess volatility and volatility clustering.

Since agent-based models are quite powerful, it seems reasonable to use them as artificial laboratories and to carry out computer experiments with them to improve our insights into the working of certain regulatory mechanisms. Some benefits of such an approach are immediately clear. One may generate as much data as needed, control for

exogenous shocks, simulate special events such as a financial market crisis, measure all variables precisely and vary the policy maker's control parameter smoothly. We seek to demonstrate that this approach may at least be regarded as an alternative to traditional economic theorizing, human subject experiments or empirical studies. However, since this research area is quite young, there are still many open issues which have to be addressed in the future. Some shortcomings, drawback and limitations will become clear in this study.

The paper is organized as follows. In section 2, we develop a simple agent-based financial market model which is quite capable to mimic the dynamics of financial markets. In sections 3 to 5, we explore the effects of transaction taxes, central bank interventions and trading halts, respectively. In the last section, we offer some preliminary conclusions and point out some avenues for future research.

2 A basic model

2.1 Motivation

A huge body of experimental evidence (Simon 1955, Kahneman, Slovic and Tversky 1986, Smith 1991) supports the notion that human agents are boundedly rational. Although people lack the cognitive capabilities to derive fully optimal actions, they should not be regarded as irrational. In fact, people strive to do the right thing. It may be more accurate to describe their behavior as rule-governed behavior. This means that people rely on a limited number of simple heuristic principles which have proven to be useful in the past. These heuristics may evolve over time, i.e. bad heuristics are erased and new ones are created. An agent's choice of a particular rule from the set of available rules in an actual decision situation may be influenced by several factors such as the

rule's past performance, its appropriateness to the current situation, or simply by the agents' social environment. Overall, these observations may be crucial to economic theory: if we are able to identify peoples' main heuristics, it may be possible to model their behavior. If we succeed in doing this, we may be able to study interactions between them and the effects of such interactions on economic variables.

Fortunately, we have these information in the case of financial markets. Questionnaire evidence (e.g. Taylor and Allen 1992, Menkhoff 1997, Lui and Mole 1998) informs us that agents rely on both technical and fundamental trading rules when determining their investment position. For short-term horizons, say of up to one week, technical and fundamental analysis are even judged to be equally important. While technical trading rules aim to derive trading signals out of past price movements (Edwards and Magee 1966, Pring 1991, Murphy 1999), fundamental trading rules bet on a reduction of the mispricing in the markets (Graham and Dodd 1951, Greenwald et al. 2001). Similar results have been observed in asset pricing experiments in which agents adhere to extrapolative and regressive prediction rules (Caginalp et al. 2001, Sonnemans et al. 2004, Hommes et al. 2005). Recall that we frequently observe bubbles and crashes in laboratory experiments, which again suggests that these phenomena are endogenously created by the agents involved.

In recent years, several financial market models have been proposed which explore interactions between heterogeneous boundedly rational agents. Although it is not our goal to review this line of research, key contributions include Day and Huang (1990), Kirman (1991), Chiarella (1992), de Grauwe et al. (1993), Lux (1995), Brock and Hommes (1998), LeBaron et al. (1999) and Farmer and Joshi (2002). Recent surveys can be found in Hommes (2006), LeBaron (2006), Lux (2008) and Westerhoff

(2008). Since this approach involves technical and fundamental traders, it is sometimes called the chartist-fundamentalist approach.

In a nutshell, the central insight of these models is as follows: since technical traders extrapolate past price changes, they add a positive feedback to the dynamics and are likely to destabilize the market. Fundamental traders place orders on a reduction of the mispricing in the market and usually create a stabilizing mean reversion effect. The interplay between the traders may lead to complex endogenous dynamics. When technical analysis governs the market, we may observe the start of a bubble. When the market is dominated by fundamental traders, the price adjusts towards its fundamental value. Due to the fact that agents may switch between trading rules, e.g. due to profit differences or herding effects, use nonlinear trading rules or exit markets, there are in fact recurrent episodes where either technical or fundamental trading drives the market.

2.2 Setup

The structure of our model is roughly as follows. We consider a stylized speculative market which may represent a stock, foreign exchange or commodity market (see Westerhoff and Dieci 2006 for a closely related two-market scenario). The price in this market is adjusted with respect to excess demand in the usual way. Market participants have the choice between three alternatives. They may conduct either technical or fundamental analysis to determine their trading positions or they may abstain from the market. The agents' choice depends on the strategies' success in the recent past. For instance, if agents observe that technical analysis was unprofitable in the most recent trading periods, the number of agents following such trading rules will decrease. Agents update their trading decisions every time step.

Let us now turn to the details of the model. We model the price adjustment process by a so-called price impact function (Farmer and Joshi 2002). Such a function describes the relation between the quantity of an asset bought or sold in a given time interval and the price change caused by these orders. Accordingly, the log of the price of the asset in period $t+1$ is given as

$$P_{t+1} = P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t, \quad (1)$$

where a is a positive price adjustment coefficient, D^C and D^F stand for orders generated by technical and fundamental trading rules and W^C and W^F denote the fractions of agents using these rules. Hence, if excess demand is positive, prices rise. One may interpret (1) as a stylized description of the behavior of risk-neutral market makers who mediate transactions out of equilibrium and adjust prices with respect to excess demand. Since our model only provides a simple representation of real markets, we add a random term to (1). α is an IID normal random variable with mean zero and constant standard deviation σ^α .

The idea of technical analysis is to exploit price trends. When prices increase, technical analysis suggests buying the asset. Orders triggered by technical trading rules may be written as

$$D_t^C = b(P_t - P_{t-1}) + \beta_t. \quad (2)$$

The first term of the right-hand side of (2) stands for transactions triggered by an extrapolation of the current price trend. b is a positive reaction parameter and captures how strongly the agents react to this signal. The second term reflects additional random orders to account for the large variety of technical trading rules (see Murphy 1999). β is an IID normal random variable with mean zero and constant standard deviation σ^β .

Fundamental analysis presumes that prices may run away from fundamental values in the short run. In the long run, however, prices are expected to converge towards their fundamental values. Fundamental analysis suggests buying (selling) the asset when the price is below (above) its fundamental value. Orders due to fundamental trading rules may be formalized as

$$D_t^F = c(F_t - P_t) + \gamma_t, \quad (3)$$

where c is a positive reaction parameter and F is the log of the fundamental value (e.g. Day and Huang 1990). Note that agents are aware of the asset's true fundamental value. In order to allow for perception errors or deviations from the strict application of the deterministic part of (3), we include a random term in the demand function. γ is an IID normal random variable with mean zero and constant standard deviation σ^γ .

For the moment, we assume that the fundamental value is constant, i.e. we set

$$F_t = 0. \quad (4)$$

Alternatively, one may model the evolution of the fundamental value as a random walk, which we will indeed perform later in section 5.

Recall that the agents have three alternatives. Besides relying on technical and fundamental trading rules, they may also be inactive. Inspired by Brock and Hommes (1998), we assume that this choice depends on the strategies' attractiveness. The more attractive a strategy, the more agents will follow it. The following fitness functions capture the attractiveness of the three strategies

$$A_t^C = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^C + dA_{t-1}^C, \quad (5)$$

$$A_t^F = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^F + dA_{t-1}^F \quad (6)$$

and

$$A_t^O = 0, \quad (7)$$

respectively. The attractiveness of a strategy depends on two components. First, the agents take into account the most recent performance of the rules, indicated by the first terms of the right-hand side. Note here the timing of the model. Orders submitted in period $t-2$ are executed at the price stated in period $t-1$. Whether or not these orders produce myopic profits depends on the realized price in period t . Second, the agents have a memory. The memory parameter $0 \leq d \leq 1$ measures how quickly current myopic profits are discounted for strategy selection. For the extreme case $d = 0$ ($d = 1$), agents have no (a perfect) memory. We set the fitness of being inactive to zero.

Finally, we have to fix how agents select a strategy. Following Manski and McFadden (1981), the relative weights of the strategies are determined as

$$W_t^C = \frac{\exp[eA_t^c]}{\exp[eA_t^c] + \exp[eA_t^F] + \exp[eA_t^O]}, \quad (8)$$

$$W_t^F = \frac{\exp[eA_t^F]}{\exp[eA_t^c] + \exp[eA_t^F] + \exp[eA_t^O]} \quad (9)$$

and

$$W_t^O = \frac{\exp[eA_t^O]}{\exp[eA_t^c] + \exp[eA_t^F] + \exp[eA_t^O]}, \quad (10)$$

respectively. Note that the higher the fitness of a strategy, the more agents will rely on it. Parameter $e \geq 0$ captures how sensitive the mass of traders is to selecting the most attractive strategy. The higher e , the more agents will select the strategy with the highest fitness. For $e = 0$, all agents are divided evenly across the strategies, while for $e = +\infty$, all agents select the strategy with the best performance. In this sense, we may interpret e as a (bounded) rationality parameter.

2.3 Calibration, dynamics and stylized facts

Unless otherwise stated, we make use of the following parameter setting:

$$a = 1, b = 0.04, c = 0.04, d = 0.975, e = 300,$$

$$\sigma^\alpha = 0.01, \sigma^\beta = 0.05, \text{ and } \sigma^\gamma = 0.01.$$

The parameters have been selected such that the model may mimic the dynamics of actual financial markets. Such a trial and error calibration may be a time consuming exercise. Recently, some authors (Gilli and Winker 2003, Westerhoff and Reitz 2003, Alfarano et al. 2005, Boswijk et al. 2007, Manzan and Westerhoff 2007, Winker et al. 2007) have attempted to estimate models with heterogeneous interacting agents. From some of these studies we may infer that the reaction parameters of the technical and fundamental trading rule (multiplied with the price adjustment parameter) are between 0 and 0.1 for daily data. Much guidance for the other parameters is, unfortunately, not available. We think that it is reasonable to assume that technical analysis is associated with a higher noise level than fundamental analysis. To obtain interesting dynamics, one has then to find parameter values for d and e such that the relative importance of the strategies varies slowly over time (see the discussion below). In our case, this implies that agents have a rather good memory. One should note that direct parameter estimation instead of calibration may be quite elaborate. As we will see later, this is a pity since the determination of an “optimal” policy rule may depend on the model’s parameters. More progress in this important research area would be most welcome.

Figure 1 shows a snapshot of the dynamics, i.e. a single “representative” simulation run. The top panel presents the evolution of the log of the price and its fundamental value for 5000 periods, and the central panel displays the corresponding return time series. The bottom panel visualizes the trading strategies applied by the

agents, where the black, white and gray shaded areas indicate the relative impact of chartists, inactive traders and fundamentalists, respectively. Since the model is calibrated to daily data, 5000 observations correspond to a time span of about 20 years.

As we can see, the model is able to produce bubbles and crashes. Around period 1500, for instance, the price strongly exceeds its fundamental value. In the long run, however, prices seem to track their fundamental values. Volatility is high and extreme price changes may be larger than 10 percent. Note also that periods of low volatility alternate with periods of high volatility. What is driving the dynamics? The answer is given by the bottom panel. Note that there is permanent endogenous competition between the trading strategies. A single strategy may dominate the market for a while but then its relevance decreases again. Obviously, the composition of the trading strategies has a marked impact upon the dynamics. In particular, when technical trading governs the market, volatility is high and bubbles may kick in. When fundamental analysis becomes popular, prices return to the fundamental value and then remain in that vicinity. On average, each strategy is used in about 1/3 of the time, i.e. no strategy dies out over time. Recall that the aforementioned empirical evidence on the use of technical and fundamental analysis reports that both strategies are regarded by the traders as equally important in the short run. Our model generates this observation endogenously.

----- **Figure 1 about here** -----

The price dynamics of a wide range of financial markets exhibits certain universal properties. These stylized facts include the following phenomena:

- Bubbles and crashes: asset prices regularly disconnect from their fundamental values and may trace out spectacular bubble-and-crash paths.
- Excess volatility: asset prices vary far more than their fundamental values. Even

extreme price changes may be unrelated to fundamental shocks.

- Fat tails: the distribution of returns deviates significantly from the normal distribution, and possesses fat tails. This is, for instance, revealed by excess kurtosis.
- Random walk: the evolution of asset prices appears as a random walk. In particular, the autocorrelation coefficients of raw returns are essentially zero for all lags.
- Volatility clustering: periods of low volatility alternate with periods of high volatility. Temporal correlation in volatility may last several months, as indicated by the autocorrelation function for absolute returns, which is positive and decays slowly.

In-depth discussions can be found in Lux and Ausloos (2002), Sornette (2003) and Winker and Jeleskovic (2006, 2007), among others.

Without going much into detail, we can tell that our model is able to replicate these empirical properties quite well (for a deeper analysis see Westerhoff and Dieci 2006). For instance, figure 1 already reveals that our model may generate significant bubbles and crashes and excess volatility. Moreover, an estimation of the kurtosis of the return time series reveals values that are clearly larger than 3, i.e. the distribution of the returns has fat tails. Figure 2 depicts the autocorrelation function for raw returns and absolute returns for the first 100 lags. While the autocorrelation coefficients of raw returns are usually insignificant (observe that at the first lag there is some positive, yet weak autocorrelation), the autocorrelation coefficients of absolute returns are clearly positive, and die off slowly.

----- **Figure 2 about here** -----

So far we have inspected a single time series. Figure 3 replicates the dynamics of figure 1 for four different seeds of random variables. In all four cases, the dynamics resemble the one we have already discussed. Most importantly, the endogenous

competition between the strategies leads to bubbles and crashes and excess volatility. Finally, let us check what happens if we change the parameters of the model. In figure 4, we vary parameters b and c , using the same stream of random variables as in figure 1. In the top left, we decrease c from 0.04 to 0.01. As a result, prices disconnect even more strongly from the fundamental values. The opposite occurs when c increases. The dynamics in the top right have been generated with $c = 0.07$. It seems that the impact of fundamental traders is beneficial to market stability. In the bottom left, we have set $b = 0.07$ while in the bottom right $b = 0.01$. As can be seen, if the reaction coefficient of the technical trading rule decreases, mispricing in the market becomes more pronounced. In this sense, the behavior of chartists is destabilizing. Finally, we may conclude that even if we depart somewhat from our initial parameter setting, we may still observe interesting dynamics.

----- **Figures 3 and 4 about here** -----

2.4 Outlook

The model we have presented so far is able to match the stylized facts of financial markets quite well. In addition, it should be noted that the main building blocks of the model are empirically supported. We may therefore put some trust in our agent-based financial market model and use it as a computer platform to evaluate certain regulatory policy measures. Such a procedure may have several advantages:

- We may generate as much data as needed. While empirical studies or human subject experiments have only access to limited data sets, modern computers allow us to produce millions of observations.
- We may measure all variables precisely. In reality, it is basically impossible to

- calculate the fundamental value of an asset. Within our setup, this task is quite simple.
- We may control for all exogenous shocks and simulate special events. For instance, if we are interested in how a certain policy operates during a major shift in fundamentals, we may simply define such a shift in fundamentals.
 - We may vary the impact of a regulatory policy gradually. For instance, a stock market may decide to interrupt the trading process when prices change by more than 10 percent. Empirical studies may then, of course, shed light on this specific policy. Within computer experiments, however, we are able to vary the control parameter smoothly, i.e. also explore trading halts of 8, 8.25 and 8.5 percent. There are often nontrivial effects which become visible at these finer scales.

In the remainder of the paper we seek to show that the use of agent-based models to test the effectiveness of regulatory policies may be regarded as a reasonable alternative to traditional economic theorizing, human subject experiments and empirical studies. However, open issues and problems of such an approach will also become obvious.

3 Transaction taxes

3.1 Some observations

Keynes (1936), and later also Tobin (1978), recommended introducing a transaction tax to financial markets in order to curb speculative activity. In a nutshell, their argument for transaction taxes goes as follows. For the sake of simplicity, financial market participants are divided into two groups: long-term investors who have a stabilizing impact on the dynamics and short-term speculators who have a destabilizing impact on them. Keynes and Tobin claim that a small transaction tax will have no impact on the behavior of long-term stabilizing investors but will strongly penalize short-term

destabilizing speculators. This seems natural since the more frequently a trader adjusts his portfolio, the higher the total transaction tax he has to pay. As thus concluded by Keynes and Tobin, destabilizing speculators will retreat from the market and prices will become more efficient. In the aftermath of this proposal, transaction taxes have been heavily debated and there are a number of prominent supporters, e.g. Stiglitz (1989), Summers and Summers (1989) or Eichengreen et al. (1995). For an overview and discussion of many practical issues involved in the introduction of a transaction tax, see Schwert and Seguin (1993), ul Haq et al. (1996) and Spahn (2002).

Some empirical evidence suggests that transaction taxes may not be stabilizing, including Umlauf (1993), Jones and Seguin (1997), Aliber et al. (2003) and Hau (2006). However, these empirical papers are not without problems. For instance, the paper by Umlauf (1993) is based on the case in which Sweden introduced a 2 percent transaction tax. Even the most optimistic advocates of transaction taxes nowadays no longer agree with such a high transaction tax. For a critical review of the empirical evidence, see Werner (2003). Next we investigate how transaction taxes may impact on the dynamics of our basic model.

3.2 Some results

First of all, we have to modify our model. Since the agents' selection of strategies depends on the strategies' performance, this task is rather straightforward. (5) and (6) now turn into

$$A_t^C = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^C - \text{tax}(\exp[P_t] + \exp[P_{t-1}]) | D_{t-2}^C | + dA_{t-1}^C, \quad (11)$$

and

$$A_t^F = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^F - \text{tax}(\exp[P_t] + \exp[P_{t-1}]) | D_{t-2}^F | + dA_{t-1}^F, \quad (12),$$

i.e. besides current and past myopic (gross) profits, the agents now take transaction taxes into account. The size of the transaction tax rate is indicated by the parameter tax . Consistent with the formalization of myopic profits the agents take into account that they have to pay the tax twice.

Figure 5 gives a first impression of how transaction taxes may change the dynamics of the model. Figure 5 can be directly compared with figure 1, since we use the same simulation design, including the same seed of random variables. The only difference is that agents are now confronted with a transaction tax rate of 0.3 percent. Even such a low tax rate may have a marked impact on the dynamics. The transaction tax causes the mispricing and the variability of the price to decrease.

----- **Figure 5 about here** -----

In order to obtain a more precise picture of the change in dynamics, let us define two essential statistics. As a measure of the distortion in the market we compute

$$dis = \frac{1}{T} \sum_{t=1}^T |F_t - P_t| \quad (13)$$

and as a proxy for volatility we define

$$vol = \frac{1}{T} \sum_{t=0}^T |P_t - P_{t-1}|. \quad (14)$$

The length of our data set is represented by T . In the basic model, distortion is $dis = 0.111$, while in the presence of a transaction tax of 0.3 percent it is $dis = 0.050$, that is, mispricing has decreased by about 50 percent. In comparison, volatility reduces equally sharply from $vol = 0.017$ to $vol = 0.009$.

What is going on in the model? Note that the bottom panels of figures 1 and 5 reveal that at least some agents retreat from the market due to the transaction tax. In

particular, the average market impact of technical traders decreases from about 34 percent to roughly 5 percent, while the fraction of fundamental traders remains more or less constant (see table 1 for a summary of the statistics). As revealed by further numerical analysis, the reason for this surprising result is that the profitability of the technical trading rules is driven by a higher trading volume than the profitability of the fundamental trading rule. As a result, the relative attractiveness of destabilizing technical traders decreases rather strongly. Our model thus supports the suspicion of Keynes and Tobin. One difference between their thinking and our model is that, in our setting, the agents operate on the same time scale, making the effectiveness of transaction taxes even more convincing.

----- **Table 1 about here** -----

It is now time to generalize our analysis. Figure 6 presents the impact of an increasing transaction tax on the volatility (top-left panel), the distortion (top-right panel), the average weight of technical analysis (bottom-left panel) and the average weight of fundamental analysis (bottom-right panel), respectively. The tax rate is increased in 20 discrete steps from 0 to 0.6 percent, i.e. we indeed vary this control parameter gradually. All statistics are estimated as averages over 25 simulation runs, each containing 5000 observations. With the exception of the transaction tax rate, all parameters are as in figure 1. What are the results? We see that a low transaction tax reduces both volatility and distortion. However, if the transaction tax rate is higher than about 0.3 percent, mispricing in the market increases again. Note that the higher the transaction tax, the fewer agents rely on technical analysis. In contrast, a very small transaction tax may even promote fundamental analysis. But if the tax rate is larger than about 0.1 percent, fundamentalism also declines. This explains why at some point the

distortion in the market increases again.

----- **Figure 6 about here** -----

Next we turn to the question of whether these findings are robust. In figures 7 to 9, we repeat the experiment depicted in figure 6 for different parameter combinations. We increase the memory parameter from $d = 0.975$ to $d = 0.985$ (figure 7), the rationality parameter from $e = 300$ to $e = 600$ (figure 8) and finally set both the memory parameter and the rationality parameter to the values $d = 0.985$ and $e = 600$ (figure 9). Note that in all cases, the key finding, namely that a small tax may stabilize financial markets, survives. Since the agents now have a better memory and/or are smarter, they react more sharply to the levy in the sense that they become more quickly inactive. As a result, the minimum of the distortion shifts somewhat to the left and also the following increase in the distortion is more distinct. These figures also reveal how crucial the calibration of agent-based models may be to deliver quantitative policy advice. Instead of reducing distortion with a 0.3 percent transaction tax recommendation (figure 6), the distortion may remain unchanged or even increase (figure 9).

----- **Figures 7, 8 and 9 about here** -----

3.3 Some related studies

There are now several agent-based models that explore this issue. We would like to sketch some of the crucial models and findings to illustrate the kind of insights we may get from this whole approach. It should be clear that different models provide different answers. We believe it is quite helpful to look at this problem from various angles, thereby collecting different and novel arguments for or against transaction taxes.

Let us start with Frankel (1996). He develops quite a simple exchange rate model with investors who believe that the exchange rate will return towards its

fundamental value and speculators who believe in a bubble path. Both agent types coexist in fixed proportions. Frankel analytically shows that an exogenous increase in the fraction of investors decreases the variability of the exchange rate. The opposite is true if the fraction of speculators is set higher. According to him, a transaction tax could be expected to lower the fraction of speculators or to raise the fraction of investors. Either way, it would reduce the volatility of the exchange rate in his model.

In Westerhoff (2003a), the agents switch endogenously between technical and fundamental trading rules, due to profit differentials and social interactions. This model predicts that the imposition of a small tax rate may stabilize financial markets by crowding out speculators. However, if the tax rate is set too high, distortion and volatility may increase. This nontrivial insight is caused as follows. As more and more fundamental traders leave the market, prices start to disconnect from their fundamental values. If this is the case, lasting bubbles emerge which – despite the transaction tax – may render technical trading rules profitable again.

The approach of Westerhoff and Dieci (2006) is closely related to the current setup, except that it consists of two related speculative markets. If regulators introduce a transaction tax to one of the two markets, then the taxed market becomes more stable while the untaxed market becomes more distorted and volatile. The main reason for this is that some speculators migrate from the taxed market to the untaxed market. Interestingly, if both markets impose a uniform transaction tax, volatility and distortion may decrease in both markets.

Ehrenstein et al. (2005) introduce transaction taxes into the herding model of Cont and Bouchaud (2000). Their idea is as follows. When agents retreat from the market, market liquidity decreases. When market liquidity decreases, the price impact of

a given order should increase. Hence, a transaction tax that reduces market liquidity may increase volatility via a stronger price responsiveness to the remaining excess demand. And indeed, Ehrenstein et al. (2005) find parameter constellation for which this effect may exceed the otherwise stabilizing impact of transaction taxes.

In a related yet somewhat more sophisticated paper, Mannaro et al. (2006) develop an artificial financial market model with random traders, fundamentalists, momentum traders and contrarians. What makes their approach very interesting is that, first, they model each of their 400 traders as an autonomous agent and, second, they use a price clearing mechanism that depends on demand and supply curves which, in turn, depend on the agents' orders. The key finding of the paper is as follows: transaction taxes may reduce market liquidity. As a result, the demand and supply curves are affected such that market volatility may increase.

There are further studies, e.g. the minority game approach of Bianconi et al. (2006), the noise trader models of Kupiec (1996), Palley (1999) and Song and Zhang (2005), the chartist-fundamentalist model by Demary (2006) in which traders have different investment horizons, or the comparison of different market microstructure regimes by Pellizzari and Westerhoff (2007), that reveal further interesting arguments as to why a transaction tax may or may not work.

4 Central bank interventions

4.1 Some observations

Central bank intervention is the practice of monetary authorities buying or selling currency in the foreign exchange market to influence the exchange rate, i.e. to check short-run exchange rate trends or to correct long-term deviations of the exchange rate

from its fundamental value. Central bank interventions, however, may also be profitable. For theoretical and empirical evidence see Hung (1997), LeBaron (1999), Neely (2001), Sarno and Taylor (2001), Saake (2002) or Neely (2005).

How are central bank interventions executed in practice? The decision by central banks whether and how to intervene seems to be made on a day-to-day basis. Overall, central banks have intervened quite frequently in the recent past. For instance, both the Federal Reserve Bank and the Deutsche Bundesbank intervened in the period from 1979 to 1996 every third trading day. Moreover, interventions seem to be clustered over time. The probability of intervention increases if there has been an intervention the day before. If an intervention occurred, it was small in absolute value, relative to the size of the total transactions. However, at the very moment a transaction takes place its volume hits a considerably thinner market. In addition, interventions are usually sterilized (so that the monetary base remains unchanged) and performed secretly.

Empirical studies estimating the intervention reaction function of central banks indicate that interventions are significantly influenced by past changes in the exchange rate and by deviations of the exchange rate from its fundamental value. More clearly, the central banks engage in so-called leaning against the wind interventions, that is, they buy (sell) foreign currency when the exchange rate declines (rises) to reduce or even break the momentum of the current exchange rate trend. Alternatively, they perform so-called targeting long-run fundamentals intervention, that is, they intervene in support of a target exchange rate. Similar results have been reported in the survey study of Neely (2001).

Although central banks intervene quite frequently in foreign exchange markets, at least during some past time intervals, many economists are skeptical about such

operations. Also the empirical literature is inconclusive about the usefulness of central bank interventions. In the next section, we will thus embed central bank interventions in our model and look at the issue from an agent-based perspective.

4.2 Some results

Let us start with the leaning against the wind strategy. Such a strategy may be formalized as

$$D_t^B = f(P_{t-1} - P_t), \quad (15)$$

where f is a positive reaction parameter. Using (15), the central bank seeks to counter the orders of technical traders. During a price increase, sell orders are generated and vice versa. For the sake of simplicity, the central bank intervenes every trading period. However, it would be easy to relax this assumption.

Due to the activity of the central bank, we have to correct the price adjustment function (1), which now takes the form

$$P_{t+1} = P_t + a(W_t^C D_t^C + W_t^F D_t^F + D_t^B) + \alpha_t. \quad (16)$$

Of course, the interpretation remains as before.

Figure 10 displays the impact of leaning against the wind interventions on the dynamics of the model. Figure 10 may again be compared with figure 1. The only difference is that now we set $f = 0.15$. We immediately see that the dynamics is tamed. The volatility goes down from 0.017 to 0.013. The drop in the distortion is even more pronounced, going down from 0.111 to 0.063 (see again table 1). Furthermore, extreme price changes and the size of bubbles are lower.

----- **Figure 10 about here** -----

The reason for this finding is as follows. First, central bank interventions counter

the destabilizing orders of trend extrapolators and thus slow down or even break otherwise persistent price trends. Second, central bank interventions reduce the market impact of technical traders from 34 percent to 21 percent. How does this come about? Note that the autocorrelation function shown in figure 2 reveals some minor positive autocorrelation for price change at the first lag. As a result, trend extrapolation may appear slightly profitable. However, figure 11 suggests that central bank interventions change the structure in the data. For the current parameter setting, the autocorrelation coefficient now becomes negative. This means that the central bank has destroyed some of the profit opportunities of the technical traders and even more induced the structure in the data which renders their rules unsuccessful. In reality, the impact of central bank may not be as strong as we have assumed here (which we partly did to visualize the effects) and technical traders may even modify their strategies to profit from the new structure. Nevertheless, we learn here that by eliminating price trends central banks may stabilize financial markets by (1) reducing technical trading signals and (2) making technical analysis unprofitable.

----- **Figure 11 about here** -----

In figure 12, we increase the reaction parameter of the central bank in 20 discrete steps from 0 to 0.2. The design of figure 12 is as in figure 6. Note that as the intervention parameter f increases, both volatility and distortion decrease. The bottom panels demonstrate that the impact of technical traders strongly decreases, whereas the impact of fundamental traders slightly increases.

----- **Figure 12 about here** -----

Now we turn to the targeting long-run fundamentals strategy. Applying this strategy, interventions are implemented as

$$D_t^B = g(F_t - P_t), \quad (17)$$

where g is a positive reaction parameter. This strategy resembles the trading rule of the fundamentalists, and indeed the central bank buys (sells) when the exchange rate is below (above) its fundamental value. Note that we assume that the central bank's target exchange rate is equal to the fundamental value. However, it is straightforward to change this assumption.

Figure 13 illustrates how this strategy may affect the dynamics of the model. The simulation run, which is generated with $g = 0.15$, indicates that both volatility and distortion are lower than in figure 1. In particular, bubbles and crashes have basically disappeared. How does this strategy work? The targeting long-run fundamentals strategy pushes the exchange rate closer towards its fundamental value, and thereby immediately reduces distortion. Moreover, figure 14 tells us that this strategy has an impact on the autocorrelation function of the raw returns. The autocorrelation coefficients are now somewhat negative for the first few lags. This strategy therefore also affects the profitability of technical analysis. Since the popularity of technical analysis diminishes, volatility and distortion further decline.

----- **Figures 13 and 14 about here** -----

In figure 15, we explore whether this result is robust with respect to parameter g , which is increased from 0 to 0.2. The more aggressively the central bank relies upon this strategy, the lower the distortion and volatility. While more agents use fundamental analysis, technical analysis considerably loses its followers.

----- **Figure 15 about here** -----

4.3 Some related studies

There are a few agent-based approaches that deal with central bank interventions. One of the first contributions is by Szpiro (1994). In his model, speculators believe in the persistence of bubbles. They submit buying orders in overvalued markets and selling orders in undervalued markets. The central bank does the opposite by applying the targeting long-run fundamentals strategy which, however, is nonlinear. Szpiro shows that as long as the central bank does not intervene too aggressively, the exchange rate may converge towards its fundamental value. However, when the impact of the central bank on the dynamics exceeds a critical value, a bifurcation emerges, after which the dynamics may become periodic or even chaotic. The warning is thus that a too strong response by the central bank to a misaligned market may trigger endogenous dynamics.

In Westerhoff (2001), two types of traders are considered: chartists and fundamentalists. The agents select between trading strategies depending on the condition of the market: in fear of a bursting bubble, more and more agents opt for fundamental analysis as the exchange rate deviates from its fundamental value. The findings of this model are as follows. As long as the behavior of chartists is strongly trend-extrapolating, leaning against the wind operations may reduce both volatility and distortion. However, if the behavior of chartists becomes more erratic, leaning against the wind interventions become neutral or may even decrease market stability. The reason is that if chartists' orders are largely random, the central bank is unable to counter their trades and interventions then fail in doing their job. Targeting long-run fundamentals interventions may decrease distortion but tend to increase volatility. The explanation is as follows. If the exchange rate is driven closer towards the fundamental value, the market is less mispriced and consequently a larger fraction of agents applies

technical trading rules. Hence, targeting long-run fundamentals may help reduce distortion but not volatility.

Within a nonlinear exchange rate model with chartists and fundamentalists, Wieland and Westerhoff (2005) explore whether chaos control methods can be used to stabilize foreign exchange markets. As it turns out, this may be possible. Interestingly, the analyzed chaos control methods quite closely resemble the targeting long-run fundamentals strategy.

Westerhoff and Wieland (2004) focus on the case in which technical traders may switch between different foreign exchange markets. They assume that technical traders prefer less distorted markets in order to not get caught in a bursting bubble. Both the leaning against the wind and the targeting long-run fundamentals strategies have the potential to stabilize the market in which the intervention takes place. Since this market is less distorted, it attracts some technical traders from other markets so that the other markets may also benefit from interventions. The picture changes when the central bank seeks to shift the exchange rate away from its fundamental value (e.g. to promote the national economy). Then the other markets may become destabilized since they have, on average, a higher number of technical traders.

Finally, the analysis of Reitz et al. (2006) is based on an empirical exchange rate model with interacting chartists and fundamentalists. As revealed by actual exchange rate data, fundamental traders tend to leave the market when the exchange rate runs away from its fundamental value. One explanation may be that in such a situation fundamental analysis repeatedly predicts the course of the exchange rate wrongly. Now, a central bank that applies the targeting long-run fundamentals strategy does not only drive the exchange rate towards its fundamental value but also increases the faith of

traders in fundamental analysis again. This has an additional stabilizing impact on the dynamics. Reitz et al. further show that such a strategy should only be put into action if the distance between the exchange rate and its fundamental value exceeds a critical value. They also show that such interventions may be highly profitable in the long run.

5 Trading halts

5.1 Some observations

Trading halts automatically interrupt the trading process for a given period of time when price changes are about to exceed a pre-specified limit. Policy makers hope that by interrupting an overheated market, traders are given time to cool off and reassess the situation. After the trading break, market participants may have relaxed, enabling the trading process to resume in a more orderly manner. Following the stock market crash of 1987, trading halts were introduced in numerous countries around the world, including many of the major stock markets. While policy makers apparently believe in the usefulness of trading halts, several economists remain skeptical. In the opinion of Fama (1989), financial markets are efficient and trading halts may only lead to a delayed price discovery and to a spillover of volatility. Volatility spillover means that an asset that hits a price limit in the current trading period will experience greater volatility in the next period, since the necessary price adjustment has not yet been fulfilled. For theoretical and empirical surveys of this topic, see Kyle (1988), France et al. (1994), Harris (1998), Kim and Yang (2004) and Tooma (2005).

5.2 Some results

Trading halts are embedded in the following way. The price impact function (1) is

rewritten as

$$P_{t+1} = \begin{cases} P_t - h & \text{for } P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t < P_t - h \\ P_t + h & \text{for } P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t > P_t + h, \\ P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t & \text{otherwise} \end{cases} \quad (18)$$

where h stands for the maximum allowed log price change. For instance, if $h = 0.1$, then the trading process is interrupted when log prices have either increased or decreased by 0.1 (i.e. by about 10 percent). The market reopens in the next trading period, i.e. there are no further trades in a period in which trading has been interrupted. Moreover, all orders that have not been executed are deleted.

Figure 16 gives us an impression of how trading halts may affect financial markets. In the simulation run the trading process is halted when prices change by 4 percent, i.e. $h = 0.04$. As can be seen, bubbles and crashes are less pronounced and extreme returns are limited to 4 percent. Surprisingly, trading halts seem to have virtually no impact on agents' choice of trading strategy. As more clearly indicated by table 1, the relative use of trading strategies basically remains constant, which implies that the relative profitability of technical and fundamental analysis is not very much affected.

----- **Figure 16 about here** -----

Figure 17 presents the autocorrelation function for raw returns and absolute returns. As we can see, prices still describe a random walk-like process, and volatility repeatedly switches between periods of relative calm and periods of relative turmoil. Despite the regulatory mechanism, the model is able to generate these typical time series properties. The fact that prices still evolve randomly may explain why the profitability of technical analysis does not improve or decline much.

----- **Figure 17 about here** -----

Figure 18 shows the impact of trading halts on the dynamics of our model for different values of h . To be precise, we vary h between 0 and 0.1. As trading halts become more restrictive, both volatility and distortion decline. In the extreme case of $h = 0$, volatility is completely eliminated. If we assume that the initial value of the exchange rate is identical to the fundamental value, there is also no distortion. The bottom panels of figure 18 reveal once again that the relative impact of technical and fundamental trading strategies is quite stable for different values of h . Let us now clarify how trading halts function in our model. First, there is a direct effect of trading halts on the price dynamics. For instance, if $h = 0.05$, there will be no extreme price changes larger than 5 percent, which reduces both volatility and distortion. However, there is also an important indirect effect operating here: as trading halts wipe out sharp price trends, they also destroy or at least weaken the trading signals of technical traders. Orders based on positive price trends consequently diminish, further improving market efficiency.

----- **Figure 18 about here** -----

Finally, let us discuss the case in which the fundamental value is not fixed but evolves as a random walk. For this reason, we reformulate (4) as

$$F_t = F_{t-1} + \eta_t, \tag{19}$$

where the fundamental shocks η are IID normally distributed with mean zero and constant standard deviation σ^η . In figure 19, we replicate the experiment of figure 18 but now assume that $\sigma^\eta = 0.05$ (solid lines), $\sigma^\eta = 0.1$ (dashed lines) and $\sigma^\eta = 0.2$ (dotted lines). One key finding is that in all cases volatility may be reduced by trading halts. A second important finding is that distortion may increase if trading halts are too

restrictive. The reason for this non-trivial finding is that trading halts prevent orders from both technical and fundamental traders. If the fundamental value evolves randomly, at least some orders from fundamentalists are needed for the price to be able to track its fundamental value. However, even for $\sigma^{\eta} = 0.2$, which would imply that the fundamental value changes by about 1.6 percent per trading period, a reduction in volatility and distortion is possible. Fundamental values are presumably less volatile than this and thus trading halts seem to be quite a powerful tool to stabilize financial markets. Our results thus contradict the hypothesis of a delayed price discovery process and a volatility spillover, as put forward by Fama (1989).

----- **Figure 19 about here** -----

5.3 Some related studies

Let us take a brief look at a few other contributions in this field. Westerhoff (2003b) assumes that agents switch between technical and fundamental trading rules with respect to market circumstances. On the one hand, fundamental analysis increases in popularity as a bubble builds up. On the other hand, more agents rely on technical analysis in periods of elevated volatility. In this model, trading halts manage to stabilize the markets. Of course, there is a direct effect on dynamics, as trading halts prevent extreme price changes. Moreover, there are three interesting indirect effects. First, the market becomes further stabilized, since the price signals of technical traders appear less strongly. Second, more agents rely on fundamental analysis, since the market is less volatile. While these two effects stabilize the market, the third does not. Due to the reduced distortion in the market, more agents apply destabilizing technical trading rules. Nevertheless, trading halts seem to be able to stabilize financial markets.

In the model of Westerhoff (2006), technical and fundamental traders coexist in fixed proportions. The trading strategy of fundamentalists is linear. Besides taking price signals into account, technical traders also consider the trading volume. In particular, during periods of high trading volume, price signals are regarded as rather robust and technical traders therefore become increasingly aggressive. This model may generate temporal dependence in volatility. When trading volume is high, technical traders submit a large number of orders and as a consequence, trading volume and volatility remain high. Trading halts function in the following manner. Besides the direct effect of eliminating extreme price changes, there are two additional indirect effects. First, the price signals of technical traders appear weaker. Second, since trading volume decreases, they become less aggressive. Trading halts are thus able to stabilize the dynamics in this model.

6 Conclusions

Agent-based models offer a rather new research direction to study financial market dynamics. Within these models, agents are usually regarded as boundedly rational and apply simple yet reasonable trading strategies. A key result of this approach is that interactions between agents may generate quite complex asset price dynamics. Some of the proposed models are even able to produce a price dynamic which is hard to distinguish from actual price fluctuations.

Given the apparent power of these models, the current paper explores the extent to which this approach may be used as an artificial test bed to evaluate certain regulatory policies such as transaction taxes, central bank interventions and trading halts. Using a simple financial market model, we find that these tools generally have the

potential to stabilize financial markets. They seem to reduce both distortion in the market and the volatility of prices. In addition, we report on the findings of related papers. From this exercise it should be clear that all these models offer interesting insights into the working of regulatory policies, insights that are otherwise precluded. Overall, we therefore believe that this strand of literature may sharpen our understanding of the effects of market interventions. However, there are also many competing views (and the future will hopefully produce even more). Further empirical studies may try to sort out which of these views describe reality best. And, as mentioned before, if one seeks to gain not only qualitative but also quantitative policy advice from these models, then aspects such as model validation, calibration and estimation become paramount issues.

The model we have used here for illustrative purposes is rather simple. In particular, it contains only two types of market participants. Technical traders always extrapolate the most recent price trend, whereas fundamental traders predict that the current deviation of the price from its fundamental value, which is known by agents, will decrease. The relative impact of these strategies is time-varying, depending only on the rules' success in the recent past. This model has several realistic features, but is nevertheless a quite simple representation of reality. Aspects such as the evolution of new trading strategies, the perception of the fundamental value or herding effects, among many others, have all been neglected.

This may be readdressed in the future. Let us consider the case of central bank interventions. In this paper, we assume that agents adhere to their trading rules, regardless of how central bank interventions may change price dynamics. Although central bank interventions are frequently performed secretly, we would expect that in

reality at least some agents may come up with new trading strategies as the data-generating process changes. The assumption of a fixed and inflexible set of trading rules may be regarded as even more troubling in the case of trading halts. One may also try to develop setups which model intra-day price dynamics. For instance, one could then explore in detail what may happen after a huge central bank intervention has hit the market or what may happen if the price – in a regime with trading halts – gets closer and closer towards its pre-specified limit. One may easily imagine that the traders become nervous in such a situation and that additional interesting effects may kick in. Much more work is needed to advance and improve this research direction. In particular, large type models as reviewed by LeBaron (2006) in which agents are able to learn and adjust to new trading environments should be applied to these open issues. However, we think that an initial promising start has been established in this exciting and interesting area.

References

- Alfarano, S., Lux, T. and Wagner, F. (2005): Estimation of agent-based models: The case of an asymmetric herding model. *Computational Economics*, 26, 19-49.
- Aliber, R., Chowdhry, B. and Yan, S. (2003): Some evidence that a Tobin tax on foreign exchange transaction may increase volatility. *European Finance Review*, 7, 481-510.
- Axelrod, R. and Tesfatsion, L. (2006): A guide for newcomers to agent-based modeling in the social sciences. In: Tesfatsion, L. and Judd, K. (eds.): *Handbook of computational economics Vol. 2: Agent-based computational economics*. North-Holland, Amsterdam, 1647-1659.
- Bianconi, G., Galla, T. and Marsili, M. (2006): Effects of Tobin taxes in minority game markets. Working Paper.
- Boswijk, P., Hommes, C. and Manzan, S. (2007): Behavioral heterogeneity in stock prices. *Journal of Economic Dynamics and Control*, 31, 1938-1970.
- Brock, W. and Hommes, C. (1998): Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics Control*, 22, 1235-1274.
- Caginalp, G., Porter, D. and Smith, V. (2001): Financial bubbles: Excess cash, momentum, and incomplete information. *Journal of Psychology and Financial Markets*, 2, 80-99.
- Chiarella, C. (1992): The dynamics of speculative behavior. *Annals of Operations Research*, 37, 101-123.
- Cont, R. and Bouchaud, J. (2000): Herd behavior and aggregate fluctuations in financial markets. *Macroeconomic Dynamics*, 4, 170-196.
- Day, R. and Huang, W. (1990): Bulls, bears and market sheep. *Journal of Economic Behavior and Organization*, 14, 299-329.
- De Grauwe, P., Dewachter, H. and Embrechts, M. (1993): *Exchange rate theory – chaotic models of foreign exchange markets*. Blackwell, Oxford.
- Demary, M. (2006): Transaction taxes, traders' behavior and exchange rate risks. University of Kiel, Economics Working Paper No. 2006-14.
- Edwards, R. and Magee, J. (1966): *Technical analysis of stock trends*. John Magee, Boston.
- Ehrenstein, G., Westerhoff, F. and Stauffer, D. (2005): Tobin tax and market depth. *Quantitative Finance*, 5, 213-218.
- Eichengreen, B., Tobin, J. and Wyplosz, C. (1995): Two cases for and in the wheels of international finance. *Economic Journal*, 105, 162-172.
- Fama, E. (1989): Perspectives on October 1987, or, what did we learn from the crash? In: Kampuis, R. Kormendi, R. and Watson, J. (Eds.): *Black Monday and the future of financial markets*. Irwin, Homewood, 71-82.
- Farmer, D. and Joshi, S. (2002): The price dynamics of common trading strategies. *Journal of Economic Behavior and Organization*, 49, 149-171.
- France, V., Kodres, L. and Moser, J. (1994): A review of regulatory mechanisms to control the volatility of prices. *Federal Reserve Bank of Chicago Economic Perspectives*, 18, 15-26.
- Frankel, J. (1996): How well do foreign exchange markets function: Might a Tobin tax help? NBER Working Paper 5422.
- Gilli, M. and Winker, P. (2003): A global optimization heuristic for estimating agent based models. *Computational Statistics and Data Analysis*, 42, 299-312.

- Graham, B. and Dodd, D. (1951): Security analysis. McGraw-Hill, New York.
- Greenwald, B., Kahn, J., Sonkin, P. and van Biema, M. (2001): Value investing. Wiley, New Jersey.
- Harris, L. (1998): Circuit breakers and program trading limits: What have we learned? In: Litan, R. and Santomero, A. (Eds.): Brookings-Wharton papers on financial services. Brookings Institutions Press, Washington, 17-63.
- Hau, H. (2006): The role of transaction costs for financial volatility: Evidence from the Paris bourse. *Journal of the European Economic Association*, 4, 862-890.
- Hommes, C., Sonnemans, J., Tuinstra, J. and van de Velden, H. (2005): Coordination of expectations in asset pricing experiments. *Review of Financial Studies*, 18, 955-980.
- Hommes, C. (2006): Heterogeneous agent models in economics and finance. In: Tesfatsion, L. and Judd, K. (eds.): *Handbook of computational economics Vol. 2: Agent-based computational economics*. North-Holland, Amsterdam, 1107-1186.
- Hung, J. (1997): Intervention strategies and exchange rate volatility: A noise trading perspective. *Journal of International Money and Finance*, 16, 779-793.
- Jones, C. and Seguin, P. (1997): Transaction costs and price volatility: Evidence from commission deregulation. *American Economic Review*, 87, 728-737.
- Kahneman, D., Slovic, P. and Tversky, A. (1986): *Judgment under uncertainty: Heuristics and biases*. Cambridge University Press, Cambridge.
- Keynes, J.M. (1936): *The general theory of employment, interest, and money*. Harcourt Brace, New York.
- Kim, Y. and Yang, J. (2004): What makes circuit breakers attractive to financial markets? A survey. *Financial Markets, Institutions and Instruments*, 13, 109-146.
- Kirman, A. (1991): Epidemics of opinion and speculative bubbles in financial markets. In: Taylor, M. (Ed.): *Money and financial markets*. Blackwell, Oxford, 354-368.
- Kupiec, P. (1996): Noise traders, excess volatility, and securities transaction tax. *Journal of Financial Services Research*, 10, 115-129.
- Kyle, A., 1988. Trading halts and price limits. *Review of Futures Markets*, 7, 426-434.
- LeBaron, B. (1999): Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics*, 49, 125-143.
- LeBaron, B. (2006): Agent-based computational finance. In: Tesfatsion, L. and Judd, K. (Eds.): *Handbook of computational economics Vol. 2: Agent-based computational economics*. North-Holland, Amsterdam, 1187-1233.
- LeBaron, B., Arthur, B. and Palmer, R. (1999): Time series properties of an artificial stock market. *Journal of Economic Dynamics and Control*, 23, 1487-1516.
- Lui, Y.-H. and Mole, D. (1998): The use of fundamental and technical analysis by foreign exchange dealers: Hong Kong evidence. *Journal of International Money and Finance*, 17, 535-545.
- Lux, T. (1995): Herd behavior, bubbles and crashes. *Economic Journal*, 105, 881-896.
- Lux, T. (2008): Financial power laws: Empirical evidence, models and mechanisms. In: Cioffi-Revilla, C. (ed.): *Power laws in the social sciences: Discovering complexity and non-equilibrium dynamics in the social universe*. Cambridge University Press, Cambridge, in press.
- Lux, T. and Ausloos, M. (2002): Market fluctuations I: Scaling, multiscaling, and their possible origins. In: Bunde, A., Kropp, J. and Schellnhuber, H. (Eds.): *Science of disaster: climate disruptions, heart attacks, and market crashes*. Springer: Berlin, 373-410.
- Mannaro, K., Marchesi, M. and Setzu, A. (2006): Using an artificial financial market

- for assessing the impact of Tobin-like transaction taxes. *Journal of Economic Behavior and Organization*, in press.
- Manski, C. and McFadden, D. (1981): *Structural analysis of discrete data with econometric applications*. MIT Press, Cambridge.
- Manzan, S. and Westerhoff, F. (2007): Heterogeneous expectations, exchange rate dynamics and predictability. *Journal of Economic Behavior and Organization*, 64, 111-128.
- Menkhoff, L. (1997): Examining the use of technical currency analysis. *International Journal of Finance and Economics*, 2, 307-318.
- Murphy, J. (1999): *Technical analysis of financial markets*. New York Institute of Finance, New York.
- Neely, C. (2001): The practice of central bank intervention: Looking under the hood. *Federal Reserve Bank of St. Louis Review*, 83, 1-10.
- Neely, C. (2005): An analysis of recent studies of the effect of foreign exchange intervention. *Federal Reserve Bank of St. Louis Review*, 87, 685-717.
- Palley, T. (1999): Speculation and Tobin taxes: Why sand in the wheels can increase economic efficiency. *Journal of Economics*, 69, 113-126.
- Pellizzari, P. and Westerhoff, F. (2007): Some effects of transaction taxes under different market microstructures. *Quantitative Finance Research Centre, Research Paper 212*.
- Pring, M. (1991): *Technical analysis explained*. McGraw-Hill, New York.
- Reitz, S., Westerhoff, F. and Wieland, C. (2006): Target zone interventions and coordination of expectations. *Journal of Optimization Theory and Applications* 128, 453-467.
- Saacke, P. (2002): Technical analysis and the effectiveness of central bank intervention. *Journal of International Money and Finance*, 21, 459-479.
- Sarno, L. and Taylor, M. (2001): Official intervention in the foreign exchange market: Is it effective and, if so, how does it work? *Journal of Economic Literature*, 39, 839-868.
- Schwert, W. and Seguin, P. (1993): Securities transaction taxes: An overview of costs, benefits and unresolved questions. *Financial Analyst Journal*, 49, 27-35.
- Simon, H. (1955): A behavioral model of rational choice. *Quarterly Journal of Economics*, 9, 99-118.
- Shiller, R. (2000): *Irrational exuberance*. Princeton University Press, Princeton.
- Smith, V. (1991): *Papers in experimental economics*. Cambridge University Press, Cambridge.
- Song, F. and Zhang, J. (2005): Securities transaction tax and market volatility. *Economic Journal*, 115, 1103-1120.
- Sonnemans, J., Hommes, C., Tuinstra, J. and van de Velden, H. (2004): The instability of a heterogeneous cobweb economy: A strategy experiment on expectation formation. *Journal of Economic Behavior and Organization*, 54, 453-481.
- Sornette, D. (2003): *Why stock markets crash*. Princeton University Press, Princeton.
- Spahn, B. (2002): *On the feasibility of a tax on foreign exchange transactions*. Report commissioned by the Federal Ministry for Economic Cooperation and Development, Bonn.
- Stiglitz, J. (1989): Using tax policy to curb speculative short-term trading. *Journal of Financial Services*, 3, 101-113.
- Summers, L. and Summers, V. (1989): When financial markets work too well: A cautious case for a securities transaction tax. *Journal of Financial Services*, 3, 163-

- Szpiro, G. (1994): Exchange rate speculation and chaos inducing intervention. *Journal of Economic Behavior and Organization*, 24, 363-368.
- Taylor, M. and Allen, H. (1992): The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance*, 11, 304-314.
- Tesfatsion, L. and Judd, K. (2006): *Handbook of computational economics Vol. 2: Agent-based computational economics*. North-Holland, Amsterdam.
- Tobin, J. (1978): A proposal for international monetary reform. *Eastern Economic Journal*, 4, 153-159.
- Tooma, E. (2005): Still in search for answers: a critical survey on the circuit breaker regulation. *Investment management and Financial Innovations*, 2, 39-48.
- Ul Haq, M., Kaul, I. and Grunberg, I. (1996): *The Tobin tax: Coping with financial volatility*. Oxford University Press, New York.
- Umlauf, S. (1993): Transaction taxes and the behavior of the Swedish stock market. *Journal of Financial Economics*, 33, 227-240.
- Werner, I. (2003): Comment on 'Some Evidence that a Tobin Tax on Foreign Exchange Transactions may Increase Volatility'. *European Finance Review*, 7, 511-514.
- Westerhoff, F. (2001): Speculative behavior, exchange rate volatility, and central bank intervention. *Central European Journal of Operations Research*, 9, 31-50.
- Westerhoff, F. (2003a): Heterogeneous traders and the Tobin tax. *Journal of Evolutionary Economics*, 13, 53-70.
- Westerhoff, F. (2003b): Speculative markets and the effectiveness of price limits. *Journal of Economic Dynamics and Control*, 28, 493-508.
- Westerhoff, F. (2006): Technical analysis based on price-volume signal and the power of trading breaks. *International Journal of Theoretical and Applied Finance*, 9, 227-244.
- Westerhoff, F. (2008): Exchange rate dynamics: A nonlinear survey. In: Rosser, B. (Ed.): *Handbook on Complexity Research*. Edward Elgar, Cheltenham, in press.
- Westerhoff, F. and Reitz, S. (2003): Nonlinearities and cyclical behavior: The role of chartists and fundamentalists. *Studies in Nonlinear Dynamics and Econometrics*, 7, issue 4, article 3.
- Westerhoff, F. and Wieland, C. (2004): Spillover dynamics of central bank interventions. *German Economic Review*, 5, 435-450.
- Westerhoff, F. and Dieci, R. (2006): The effectiveness of Keynes-Tobin transaction taxes when heterogeneous agents can trade in different markets: A behavioral finance approach. *Journal of Economic Dynamics and Control*, 30, 293-322.
- Wieland C. and Westerhoff, F. (2005): Exchange rate dynamics, central bank interventions and chaos control methods. *Journal of Economic Behavior and Organization* 58, 117-132.
- Winker, P., Gilli, M. and Jeleskovic, V. (2007): An objective function for simulation based inference on exchange rate data. *Journal of Economic Interaction and Coordination*, 2, 125-145.
- Winker, P. and Jeleskovic, V. (2006): The unconditional distribution of exchange rate returns: statistics, robustness, time aggregation. University of Essex, Colchester, Technical Report WP008-06.
- Winker, P. and Jeleskovic, V. (2007): Dependence of – and long memory in – exchange rate returns: statistics, robustness, time aggregation. University of Essex, Colchester, Technical Report WP011-07.

scenario	dis	vol	\bar{W}^C	\bar{W}^F	\bar{W}^O
basic model	0.111	0.017	0.344	0.355	0.301
transaction tax	0.050	0.009	0.045	0.346	0.609
LAW intervention	0.063	0.013	0.206	0.394	0.400
TARGET intervention	0.022	0.013	0.200	0.399	0.401
trading halts	0.090	0.015	0.350	0.344	0.306

Table 1: The impact of regulatory policies on key statistics. The distortion, volatility and average weights of technical traders, fundamental traders and inactive traders are computed for the basic model using the same parameter setting as in figure 1. For the other scenarios we use this parameter setting, but the transaction tax is 0.003 (corresponding to figure 5), the leaning against the wind (LAW) parameter is 0.15 (corresponding to figure 10), the targeting long-run fundamentals (TARGET) parameter is 0.15 (corresponding to figure 13) and trading halts are triggered for price changes reaching a 4 percent limit (corresponding to figure 16). All statistics are based on 20000 observations.

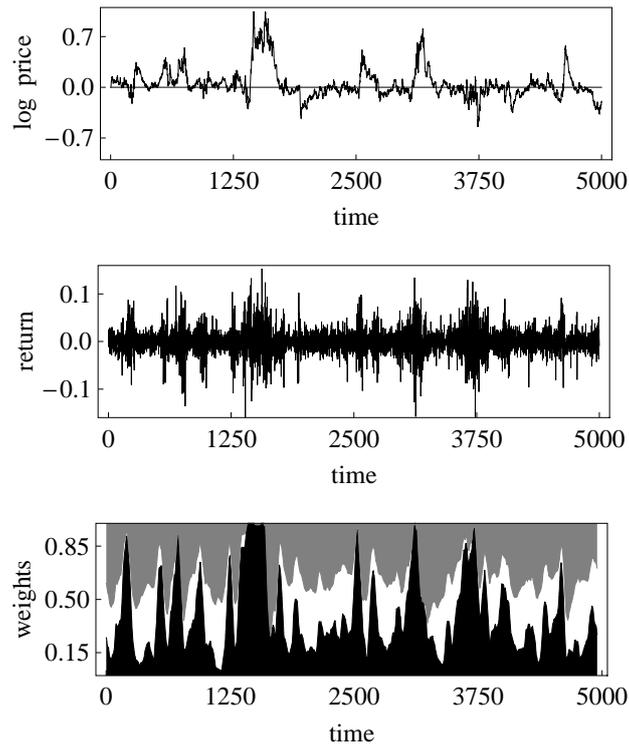


Figure 1: The dynamics of the basic model in the time domain. The panels show the evolution of the log of the price and its fundamental value, the corresponding return time series and the weights of the trading strategies (black = technical traders, white = inactive traders, grey = fundamental traders), respectively. Parameter setting as in section 2, 5000 observations.

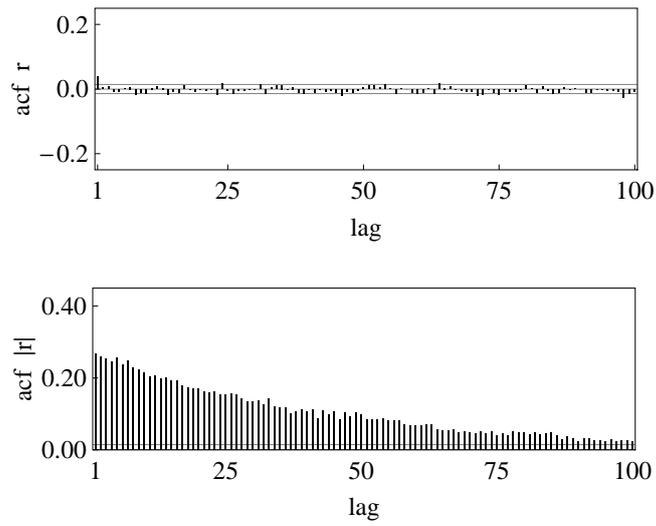


Figure 2: The autocorrelation functions for raw returns (top) and absolute returns (bottom) for the first 100 lags. Parameter setting as in figure 1, 20000 observations.

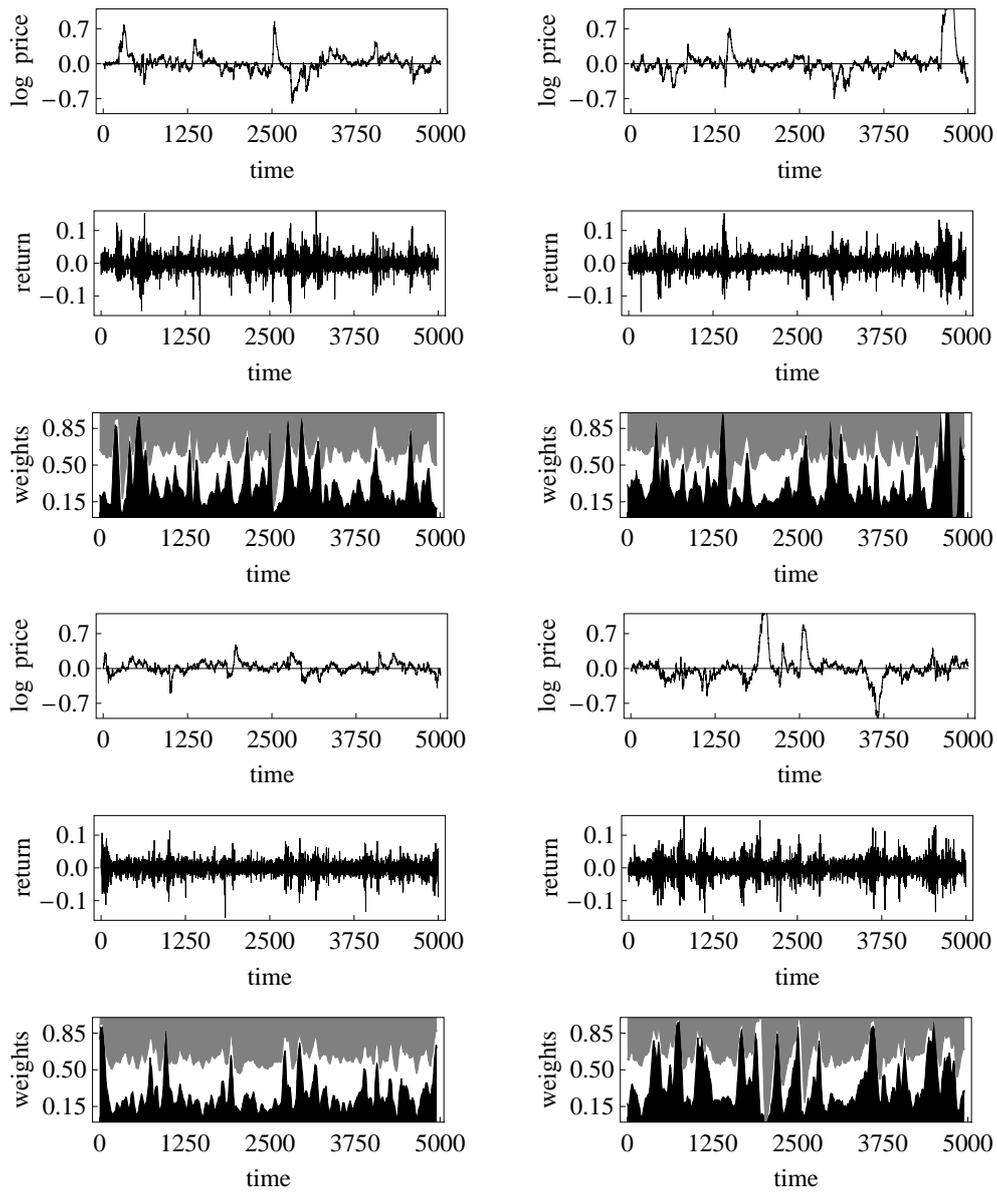


Figure 3: The dynamics of the model for different seeds of random variables in the time domain. Design and parameter setting as in figure 1.

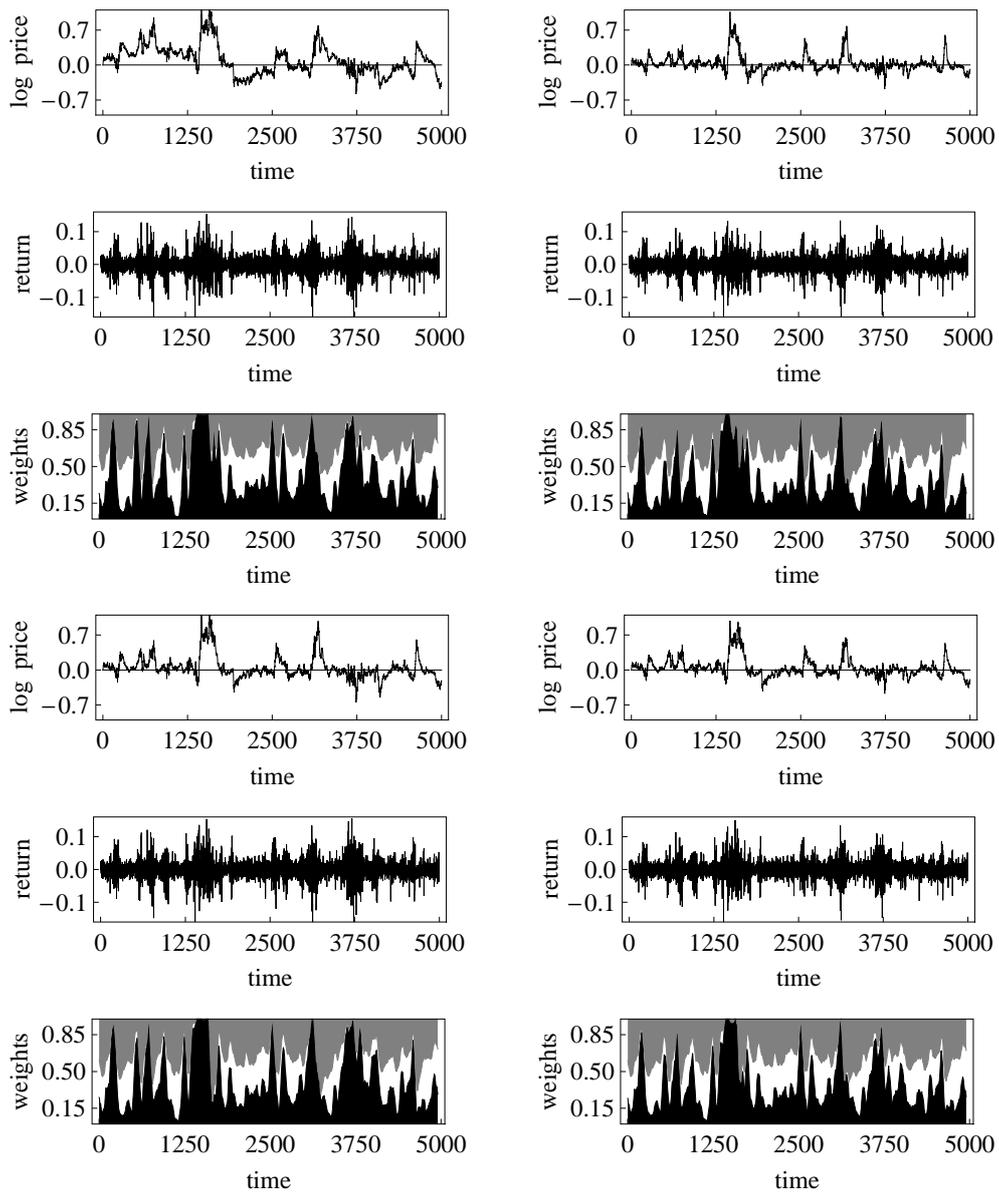


Figure 4: The dynamics of the model for different parameter values in the time domain. Design and parameter setting as in figure 1 but $c = 0.01$ (top left), $c = 0.07$ (top right), $b = 0.07$ (bottom left) and $b = 0.01$ (bottom right), respectively.

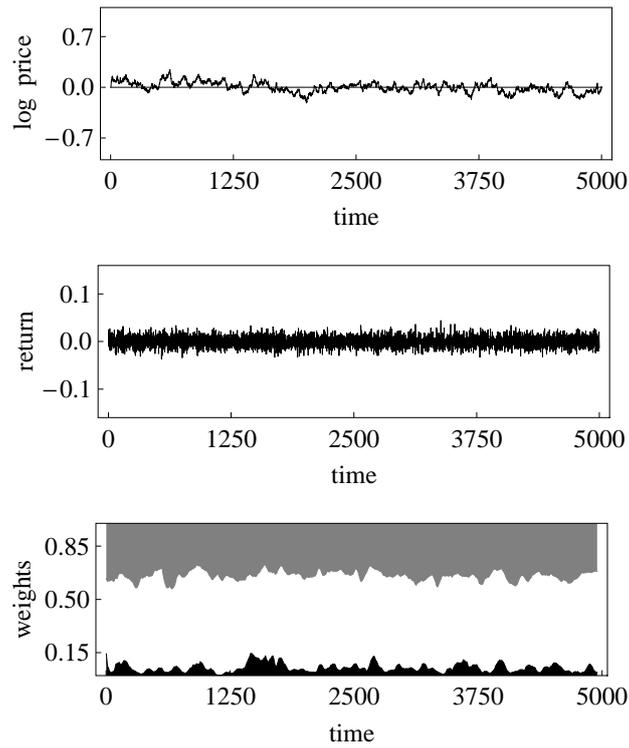


Figure 5: The dynamics of the model with transaction taxes in the time domain. Design and parameter setting as in figure 1 but $tax = 0.003$.

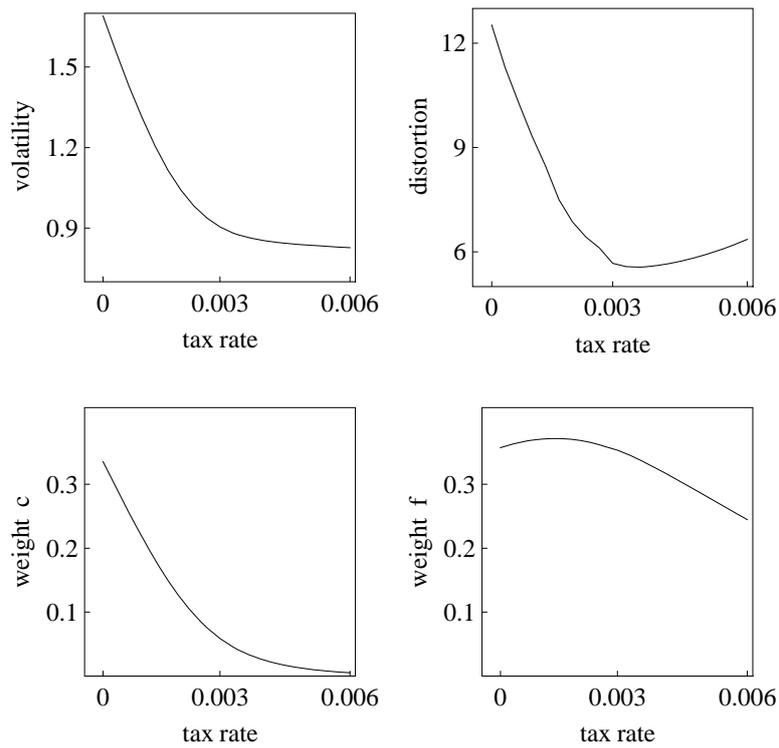


Figure 6: The impact of transaction taxes on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively. Parameter setting as in figure 1 except that the tax rate is increased in 20 discrete steps from 0 to 0.006. The statistics are estimated as averages over 25 simulation runs, each containing 5000 observations.

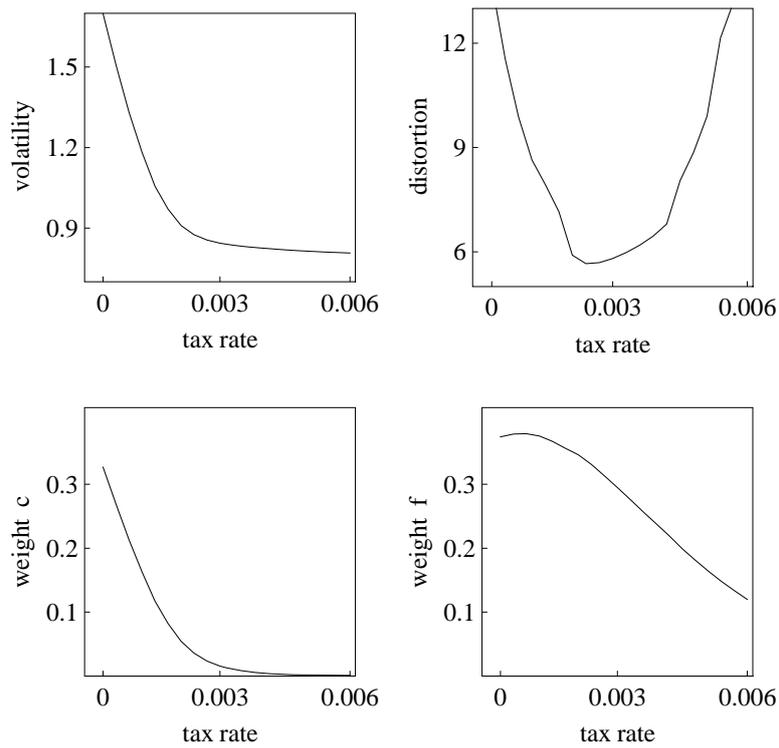


Figure 7: The impact of transaction taxes on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively, when agents have a better memory. Design and parameter setting as in figure 6 but $d = 0.985$.

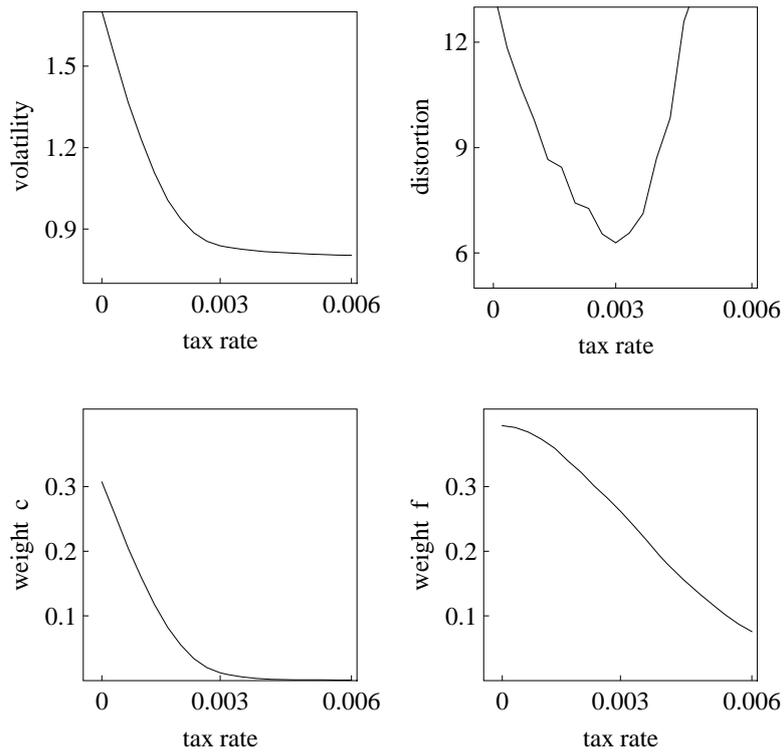


Figure 8: The impact of transaction taxes on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively, when agents are more rational. Design and parameter setting as in figure 6 but $e = 600$.

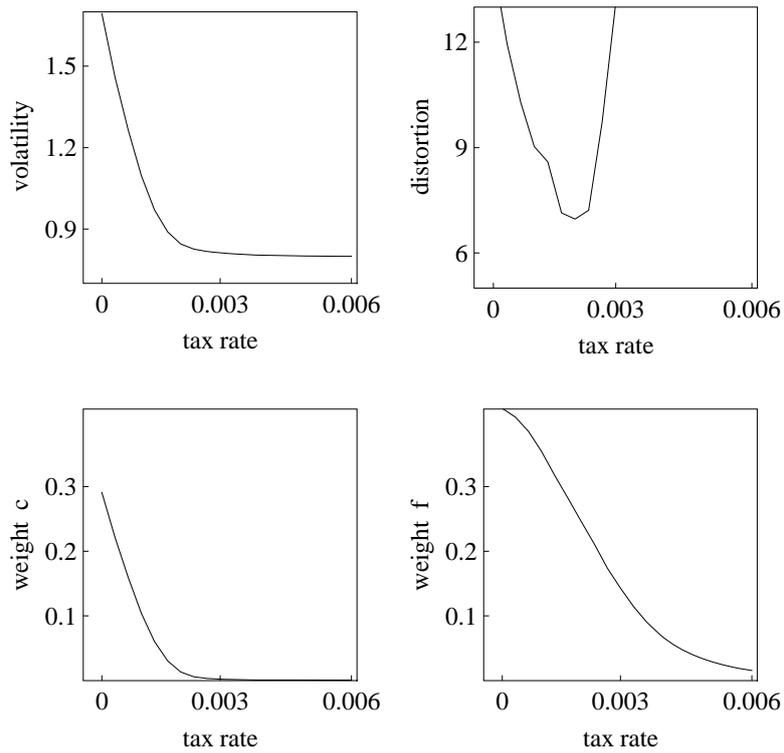


Figure 9: The impact of transaction taxes on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively, when agents have a better memory and are more rational. Design and parameter setting as in figure 6 but $d = 0.985$ and $e = 600$.

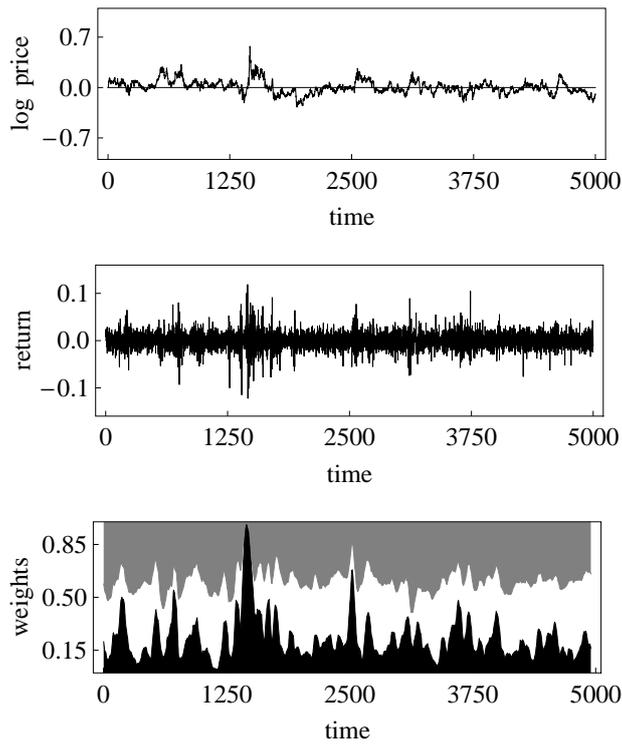


Figure 10: The dynamics of the model including leaning against the wind interventions in the time domain. Design and parameter setting as in figure 1 but $f = 0.15$.

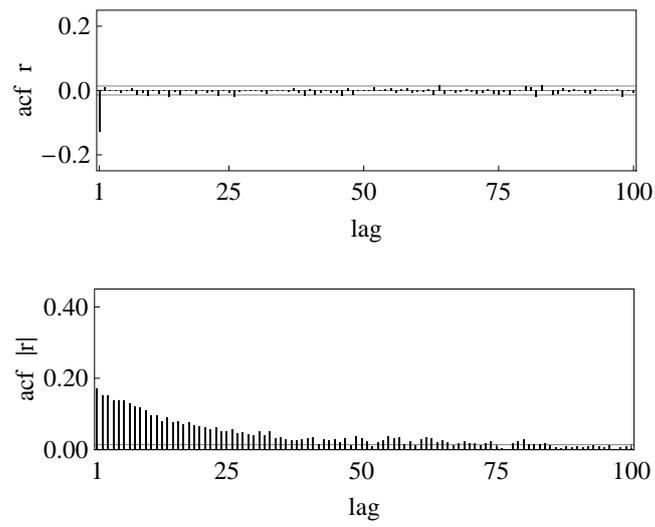


Figure 11: The autocorrelation functions for raw returns (top) and absolute returns (bottom) for the first 100 lags. Parameter setting as in figure 10, 20000 observations.

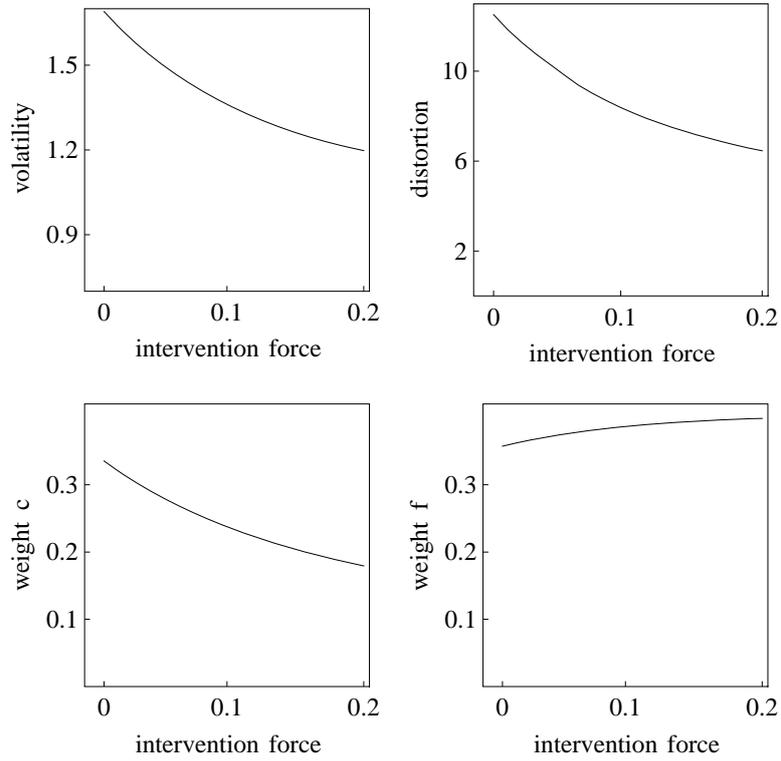


Figure 12: The impact of leaning against the wind interventions on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively. Design and parameter setting as in figure 6 but f is varied between 0 and 0.2.

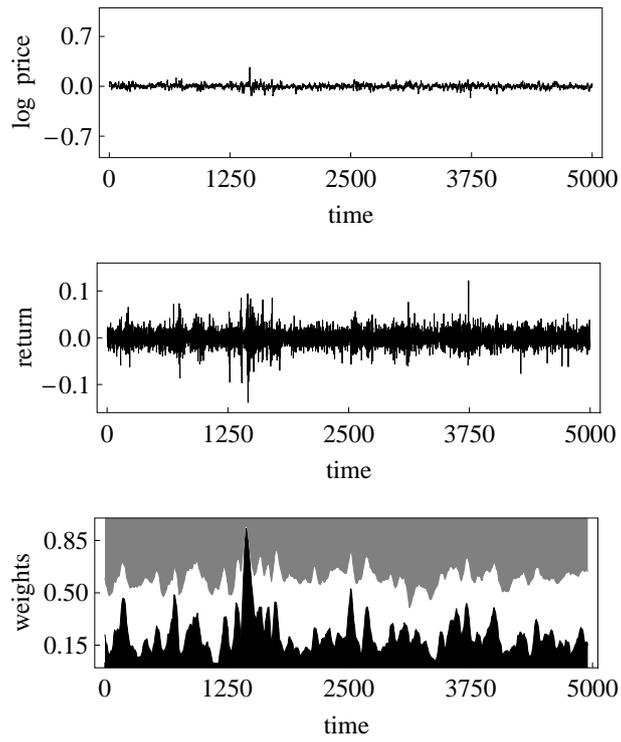


Figure 13: The dynamics of the model including targeting long-run fundamentals interventions in the time domain. Design and parameter setting as in figure 1 but $g = 0.15$.

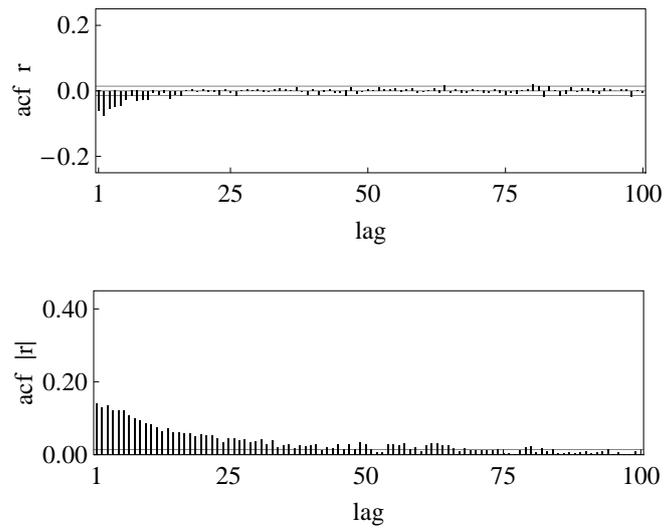


Figure 14: The autocorrelation functions for raw returns (top) and absolute returns (bottom) for the first 100 lags. Parameter setting as in figure 13, 20000 observations.

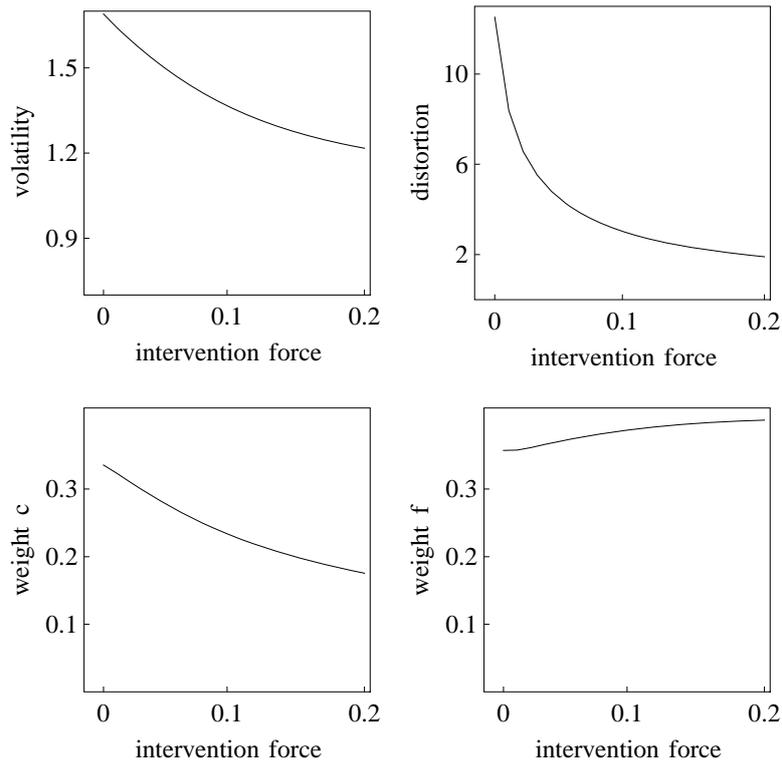


Figure 15: The impact of targeting long-run fundamentals interventions on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively. Design and parameter setting as in figure 6 but g is varied between 0 and 0.2.

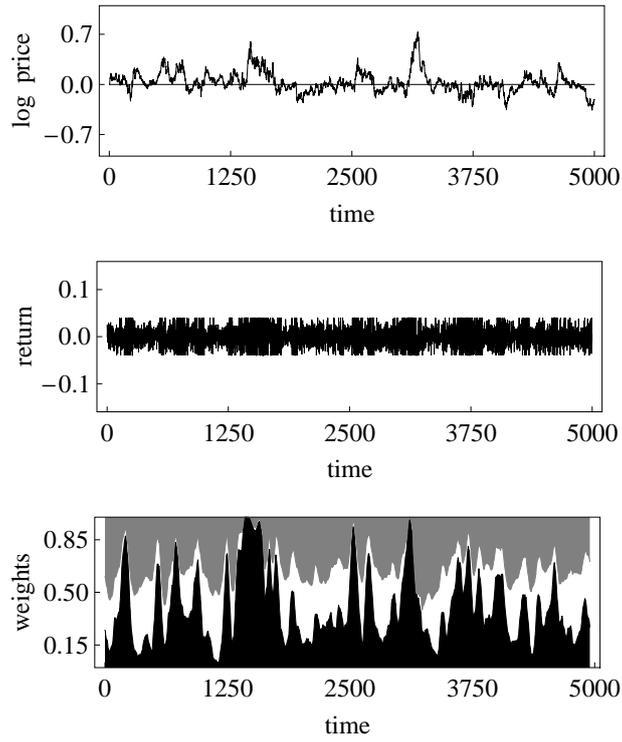


Figure 16: The dynamics of the model with trading halts in the time domain. Design and parameter setting as in figure 1 but $h = 0.04$.

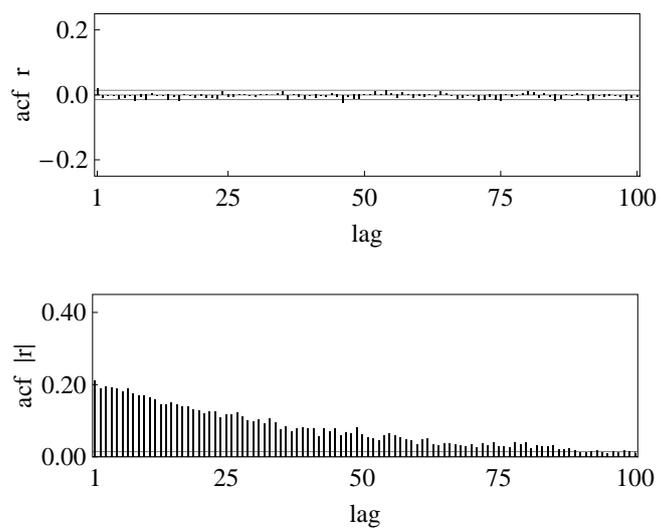


Figure 17: The autocorrelation functions for raw returns (top) and absolute returns (bottom) for the first 100 lags. Parameter setting as in figure 16, 20000 observations.

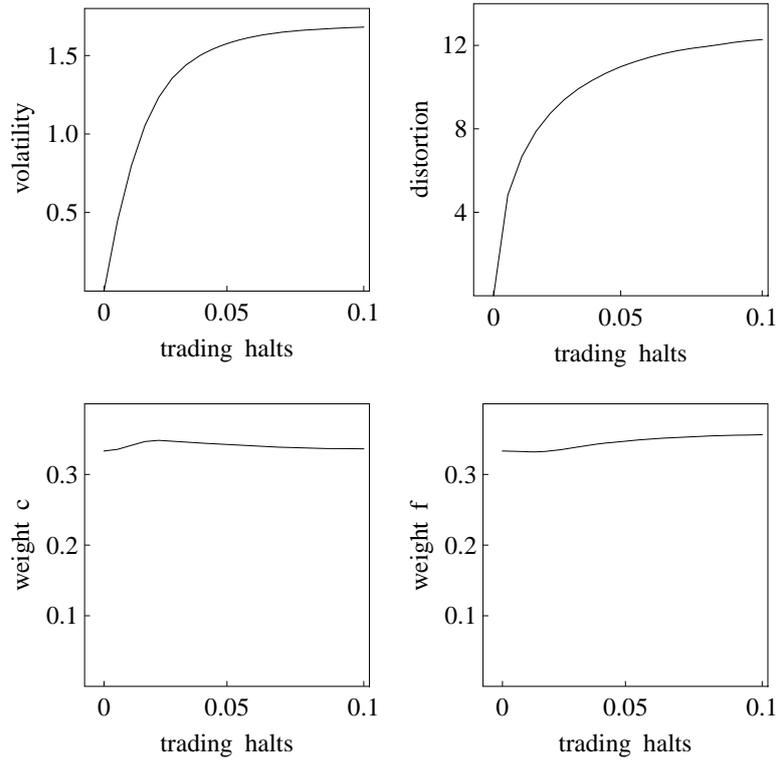


Figure 18: The impact of trading halts on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively. Design and parameter setting as in figure 6 but h is varied between 0 and 0.1.

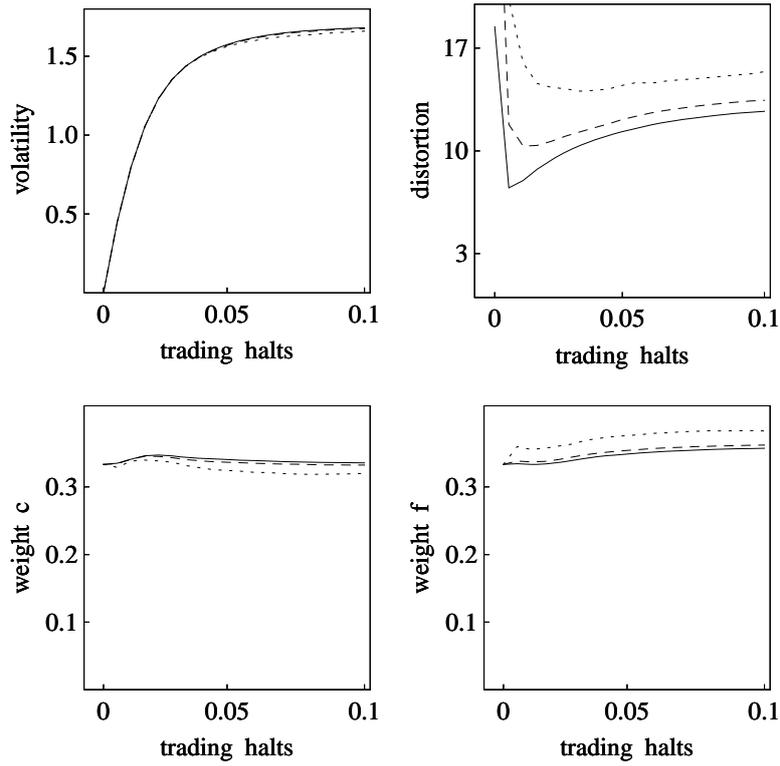


Figure 19: The impact of trading halts on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively, for different volatility levels of the fundamental value. Design and parameter setting as in figure 18 but $\sigma^\eta = 0.05$ (solid line), $\sigma^\eta = 0.1$ (dashed line) and $\sigma^\eta = 0.2$ (dotted line).