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

Frank Westerhoff (frank.westerhoff@uni-bamberg.de)

<u>General motivation</u>

- Instability of financial markets (high volatility, bubbles and crashes).
- Impact on real economy (great depression, “lost decade” in Japan, current crisis).
- Policy makers demand regulation (and in other periods deregulation).
- Agent-based models as test-beds to evaluate regulatory policies.

<u>Specific motivation</u>

- Too much and too complicated work to do. Research area needs help. From you?!
- Analytical insights, small scale competitors, large scale (AI) models, experiments.

* Westerhoff, F. (2008): The use of agent-based financial market models to test the effectiveness of regulatory policies. Zeitschrift für Nationalökonomie und Statistik (Journal of Economics and Statistics), in press.

A simple agent-based financial market model**

BB1: a price impact function

$$P_{t+1} = P_t + a(W_t^C D_t^C + W_t^F D_t^F) + \alpha_t \qquad \text{with } a > 0 \text{ and } \alpha \sim N(0, \sigma^{\alpha})$$

BB2: technical analysis

$$D_t^C = b(P_t - P_{t-1}) + \beta_t \qquad \text{with } b > 0 \text{ and } \beta \sim N(0, \sigma^{\beta})$$

BB3: fundamental analysis

$$D_t^F = c(F_t - P_t) + \gamma_t \qquad \text{with } c > 0 \text{ and } \gamma \sim N(0, \sigma^{\gamma})$$

BB4: log fundamental value

$$F_t = 0$$

** Close to Westerhoff/Dieci (JEDC, 2006).

BB5: fitness functions

$$A_t^C = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^C + dA_{t-1}^C \qquad \text{with } 0 \le d \le 1$$

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

$$A_t^O = 0$$

BB6: weights of strategies

$$W_t^C = \frac{\exp[eA_t^c]}{\exp[eA_t^c] + \exp[eA_t^F] + \exp[eA_t^O]} \qquad \text{with } e > 0$$

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

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

Calibration

Parameter setting:

$a = 1$, $b = 0.04$, $c = 0.04$,

$d = 0.975$, $e = 300$,

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

MC study reveals that model mimics the dynamics of financial markets:

(i) bubbles and crashes,

(ii) excess volatility,

(iii) fat tails for the distribution of the returns,

(iv) absences of autocorrelation in raw returns,

(v) volatility clustering.

Example

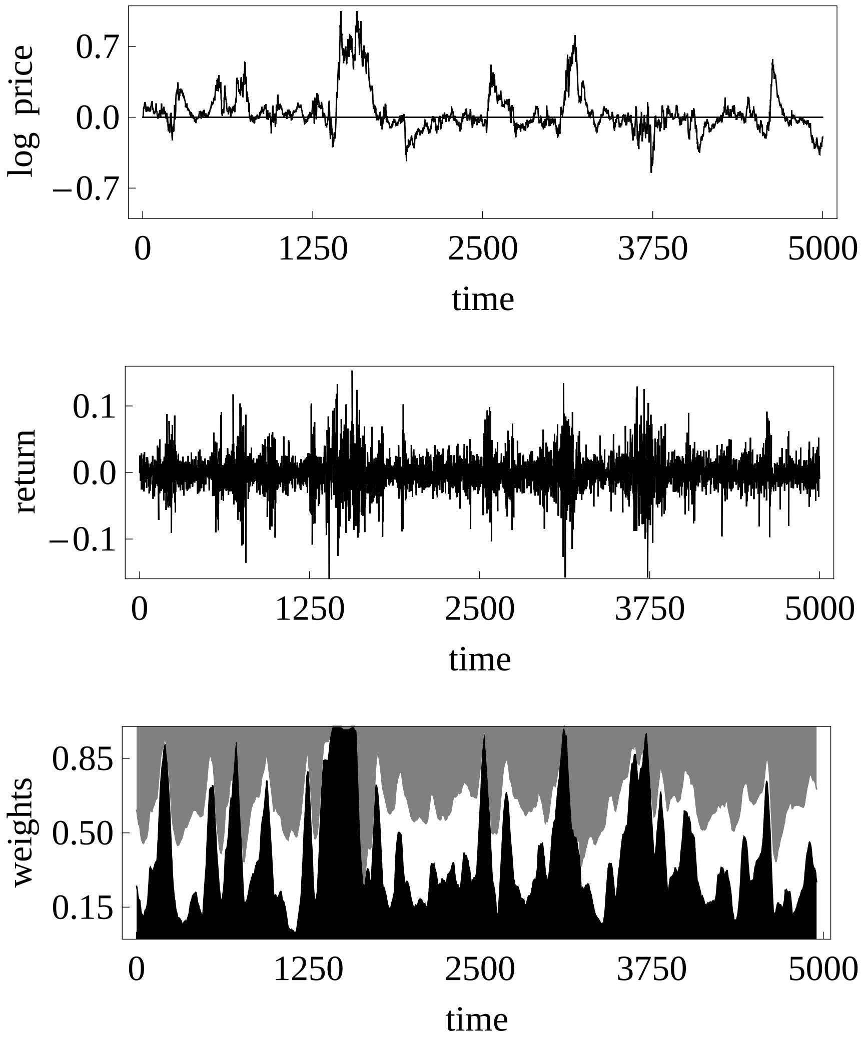


Figure 1: The dynamics of the basic model in the time domain.

Continued

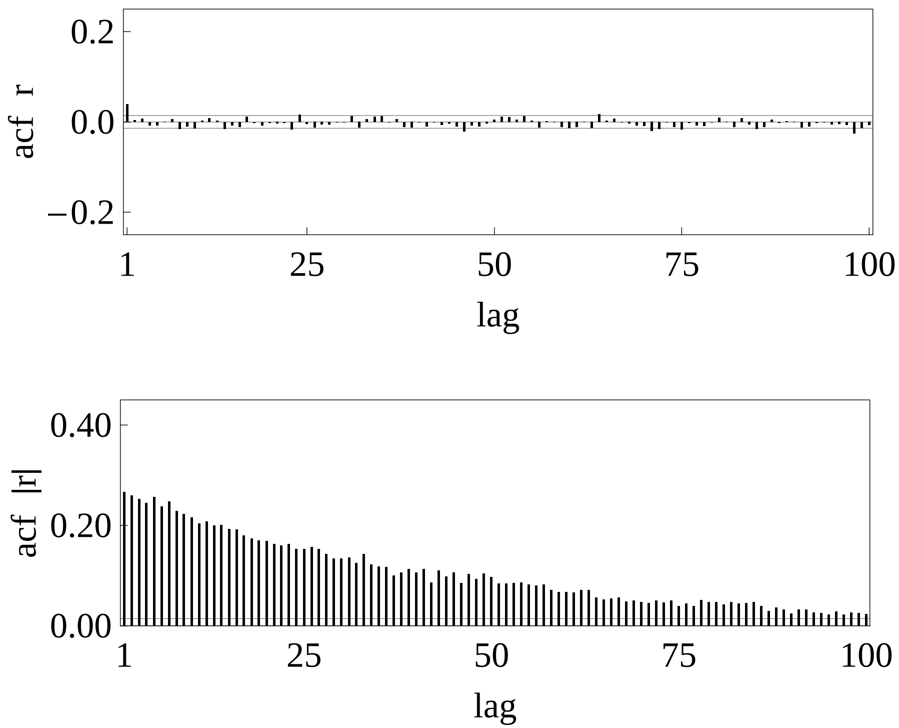


Figure 2: The autocorrelation functions for raw returns and absolute returns.

[Comment: kurtosis of returns > 3]

My impression (on this and related models):

- Main building blocks of the model are empirically supported.
- Model matches stylized facts of financial markets quite well.
- Internal dynamics seem to be reasonable.

Research goal/strategy/avenue: Use agent-based financial market models as computer platforms to evaluate regulatory policy measures!

Advantages:

- Generate as much data as needed.
- Measure all variables precisely.
- Control for all exogenous shocks.
- Study special events (e.g. extreme scenarios).
- Vary impact of a regulatory policy gradually.

Our focus:

- Transaction taxes.
- Central bank interventions.
- Trading halts.
- …

Transaction taxes

Implementation of transaction taxes

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

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

$$A_t^O = 0$$

with *tax* as the transaction tax rate

Example

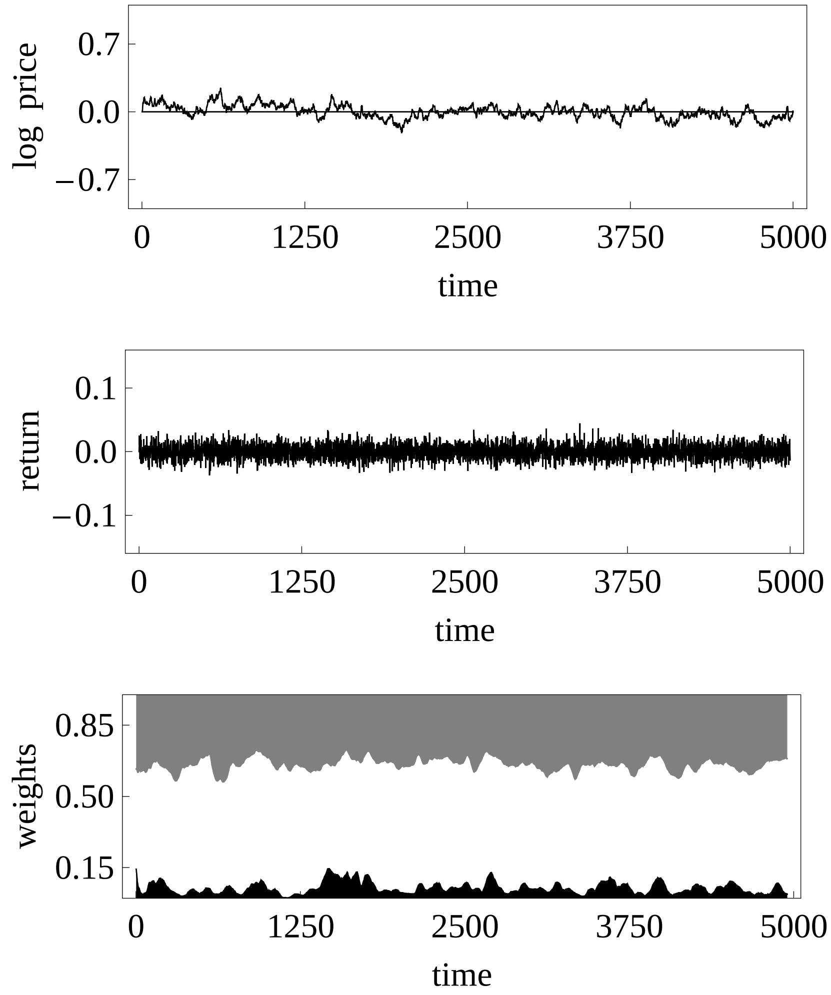


Figure 5: The dynamics with transaction taxes ($tax = 0.003 = 0.3\%$).

Market efficiency

a measure of distortion:

$$dis = \frac{1}{T} \sum_{t=1}^{T} \left| F_t - P_t \right|$$

basic model: $dis = 0.111$

tax of 0.3 %: $dis = 0.050$

a measure of volatility:

$$vol = \frac{1}{T} \sum_{t=0}^{T} \left| P_t - P_{t-1} \right|$$

basic model: $vol = 0.017$

tax of 0.3 %: $vol = 0.009$

Results

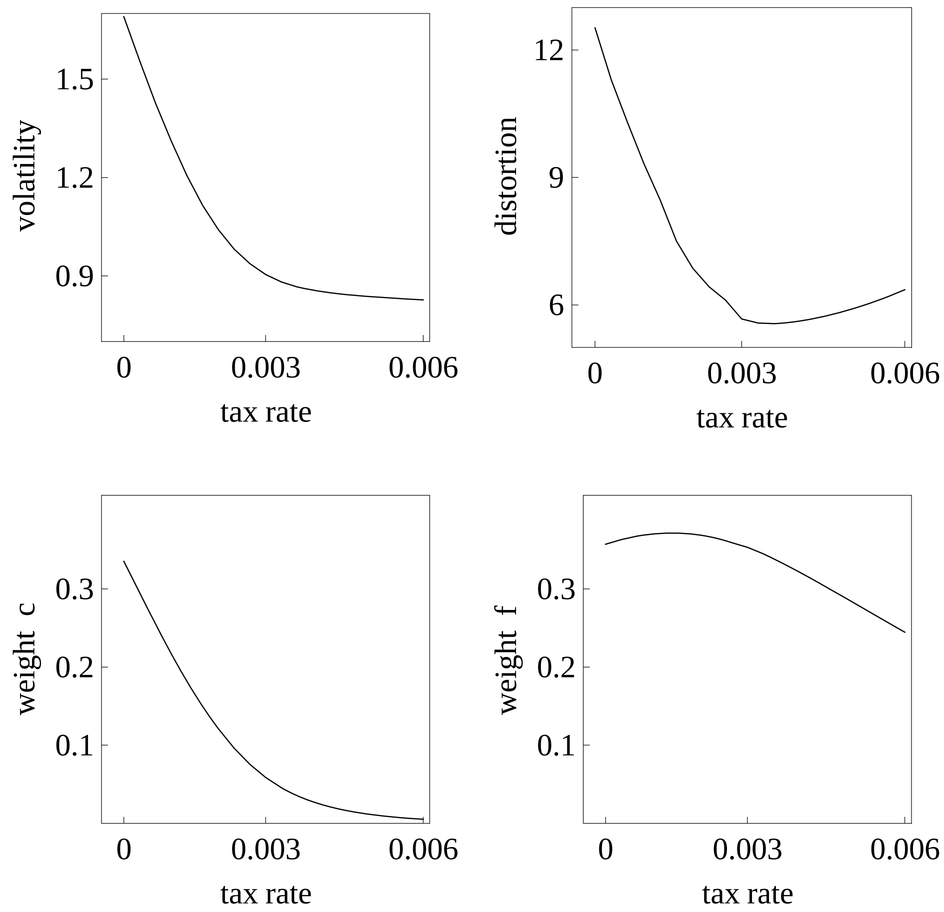


Figure 6: The impact of transaction taxes on volatility, distortion, weight of technical traders and weight of fundamental traders, respectively.

Robustness

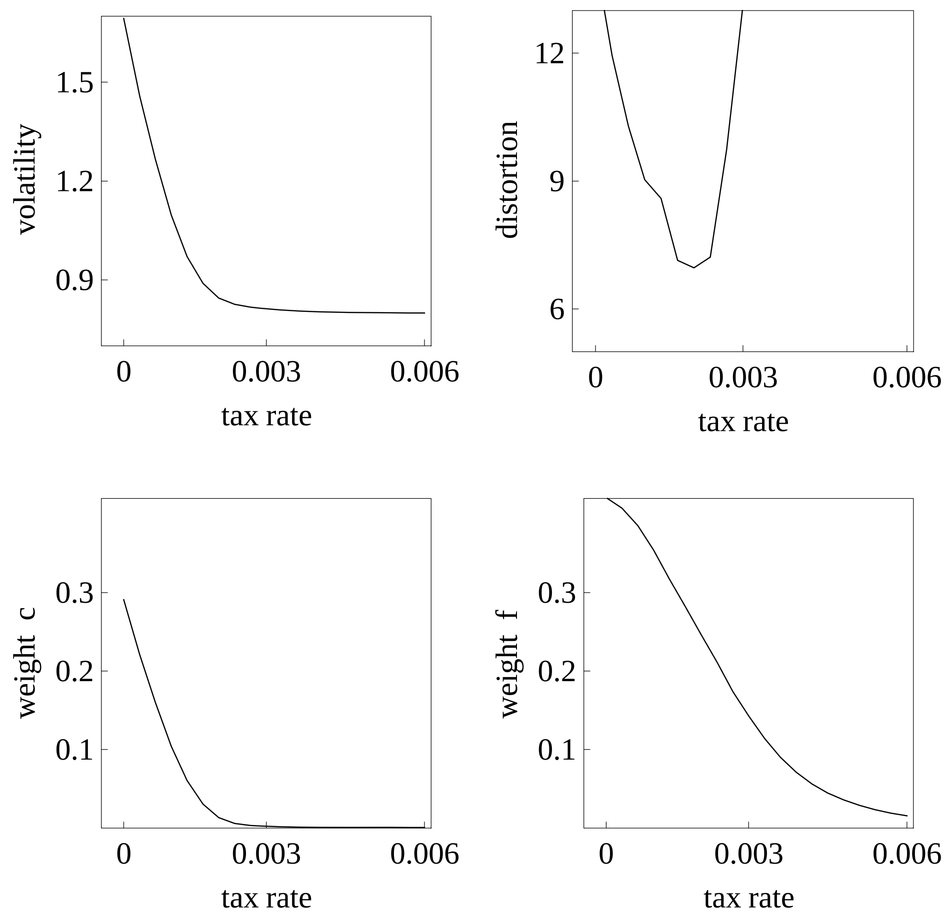


Figure 9: Agents have a better memory and are more "rational". Design and parameter setting as in figure 6 but $d = 0.985$ and $e = 600$.

Central bank interventions

Implementation of the "leaning against the wind strategy":

$$D_t^B = f(P_{t-1} - P_t) \qquad \text{with } f > 0$$

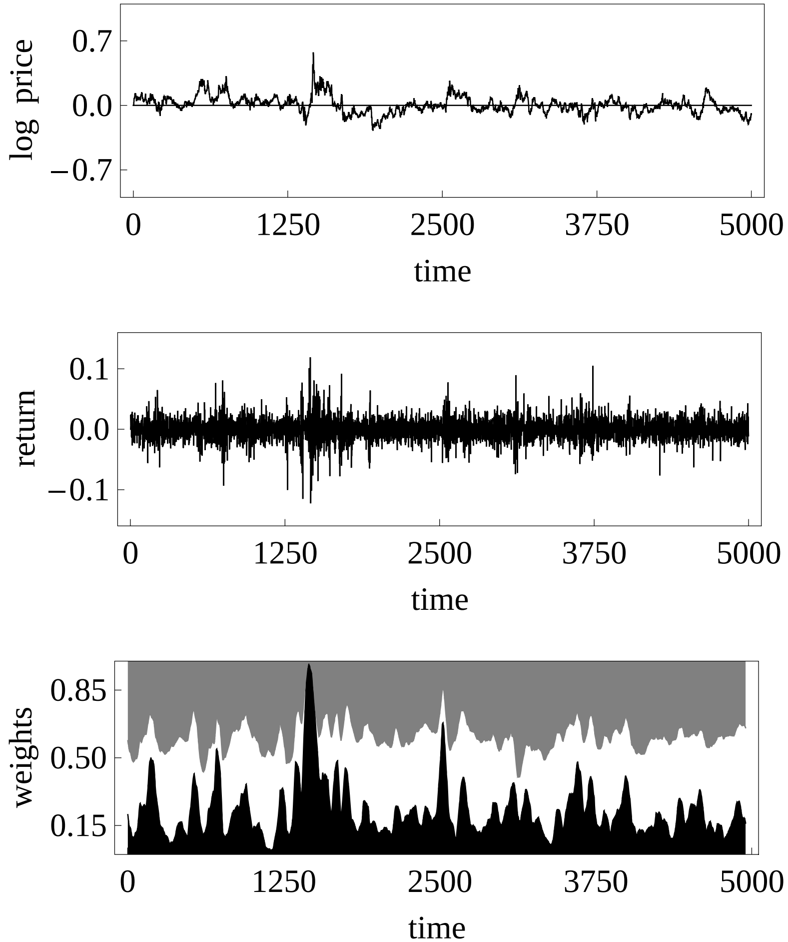
Implementation of the "targeting long-run fundamentals strategy":

$$D_t^B = g(F_t - P_t) \qquad \text{with } g > 0$$

Implications for price impact function:

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

<u>Example for LAW</u>



Insights:
- Price trends are broken.
- Trading signals disappear.
- TA turns unprofitable.

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

Background on LAW

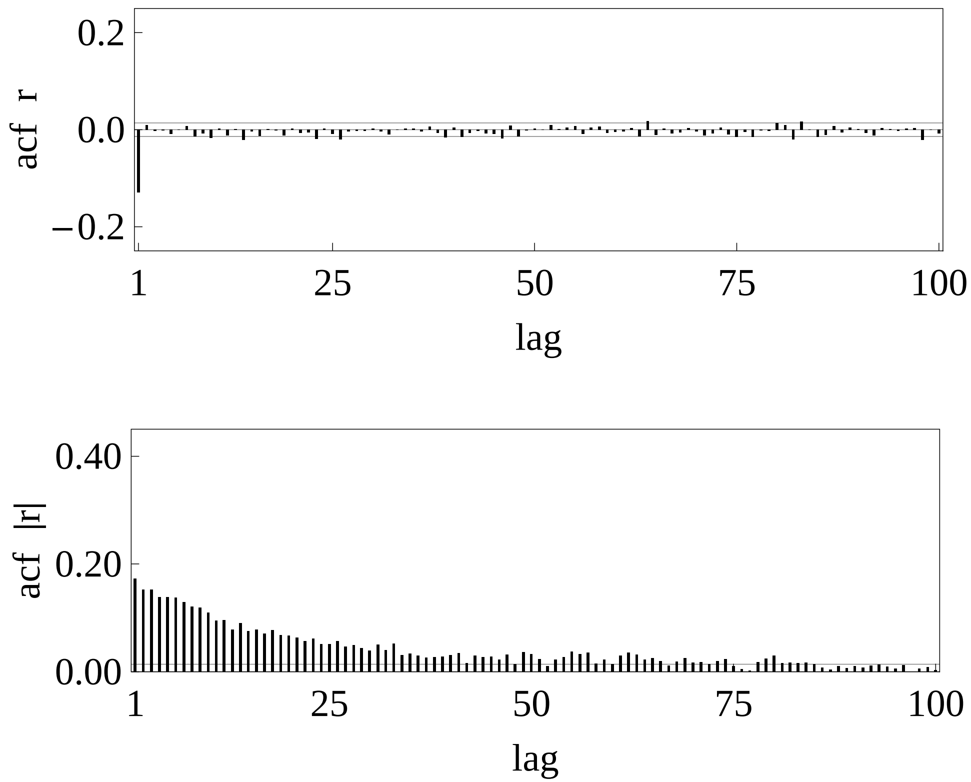


Figure 11: The autocorrelation functions for raw returns and absolute returns for the first 100 lags. Parameter setting as in figure 10.

Results for LAW

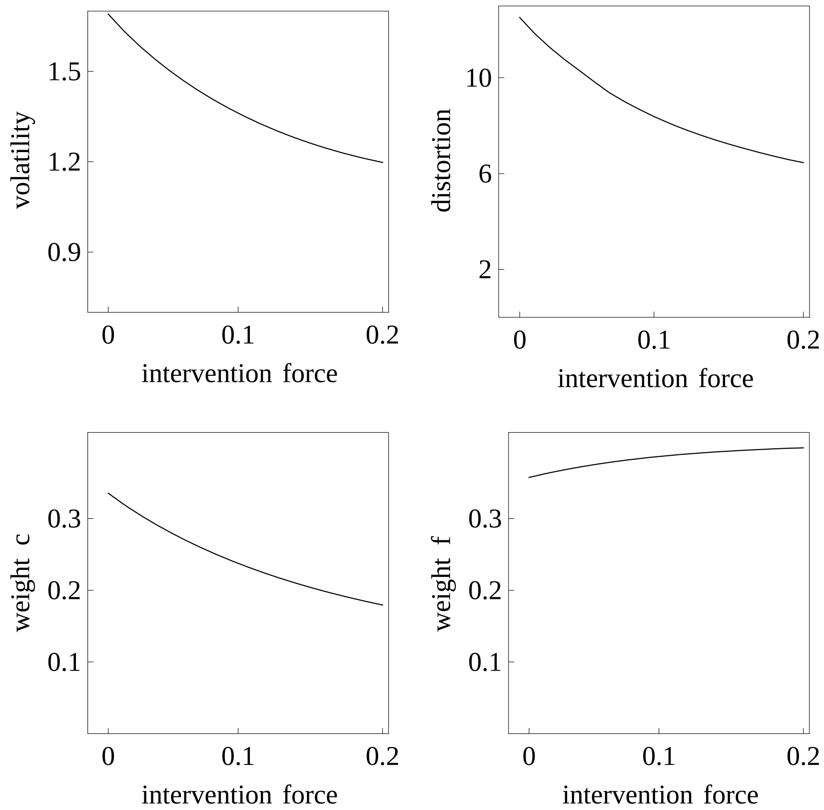


Figure 12: The impact of leaning against the wind interventions on volatility, distortion, weight of technical traders and weight of fundamental traders. Design and parameter setting as in figure 6 but f is varied between 0 and 0.2.

Example for TARGET

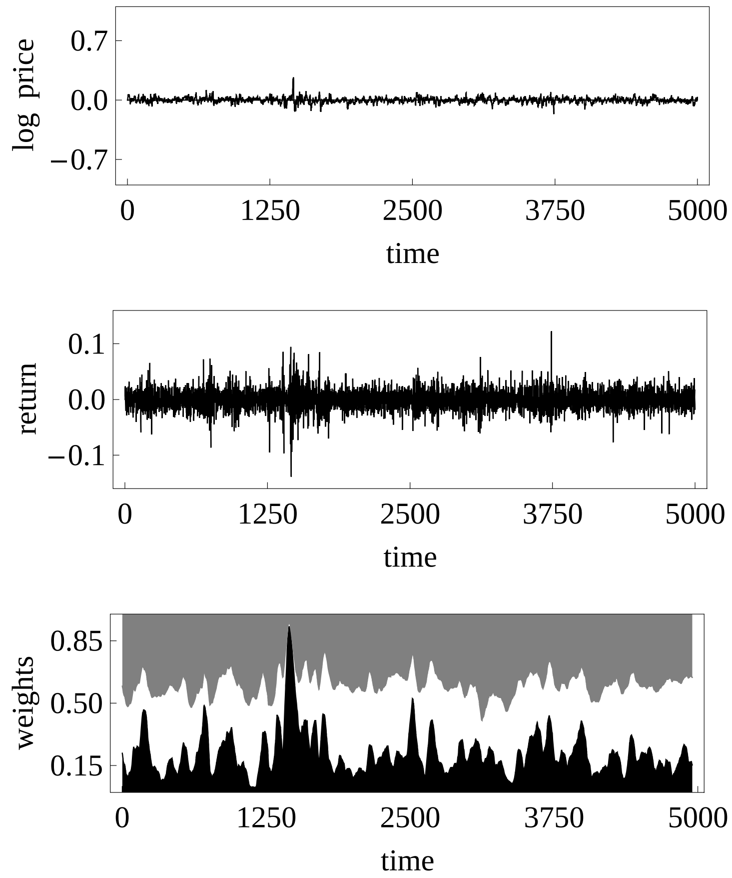


Figure 13: The dynamics of the model including targeting long-run fundamentals interventions. Design and parameter setting as in figure 1 but $g = 0.15$.

Background on TARGET

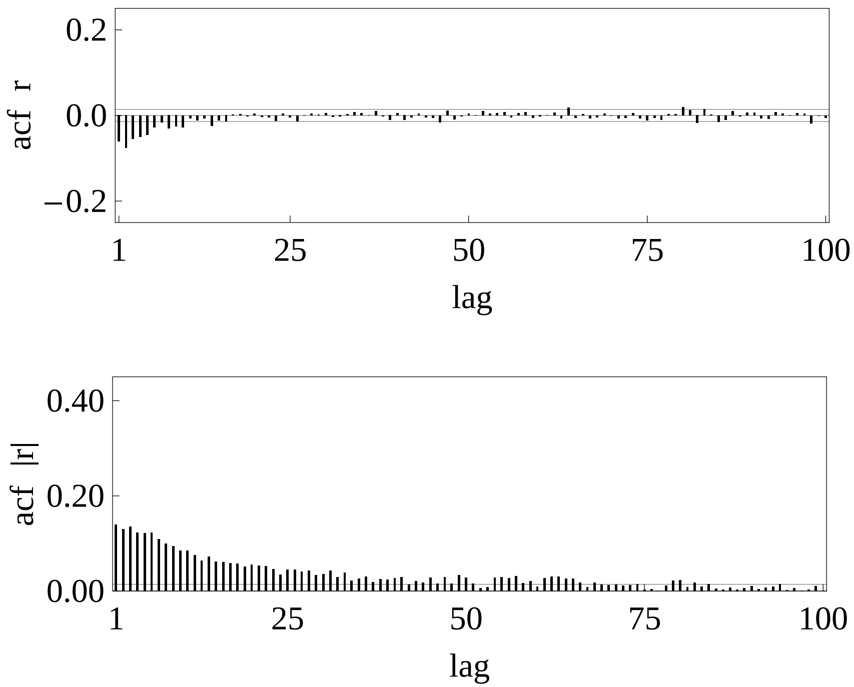


Figure 14: The autocorrelation functions for raw returns and absolute returns for the first 100 lags. Parameter setting as in figure 13, 20000 observations.

Results for TARGET

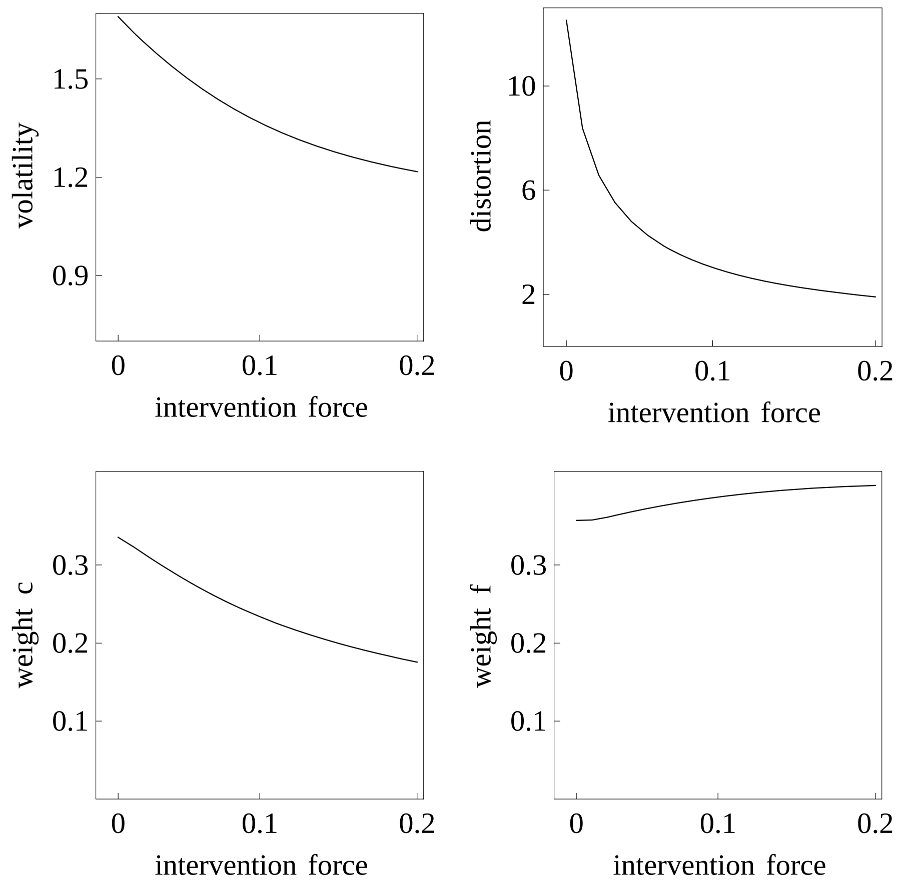


Figure 15: The impact of targeting long-run fundamentals interventions on volatility, distortion, weight of technical traders and weight of fundamental traders. Design and parameter setting as in figure 6 but g is varied between 0 and 0.2.

Trading halts

Implementation of trading halts (via rewriting price impact function):

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

where h stands for the maximum allowed log price change.

Example: If $h = 0.1$, then the trading process is interrupted when log prices have either increased or decreased by 0.1 (i.e. by 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.

Example

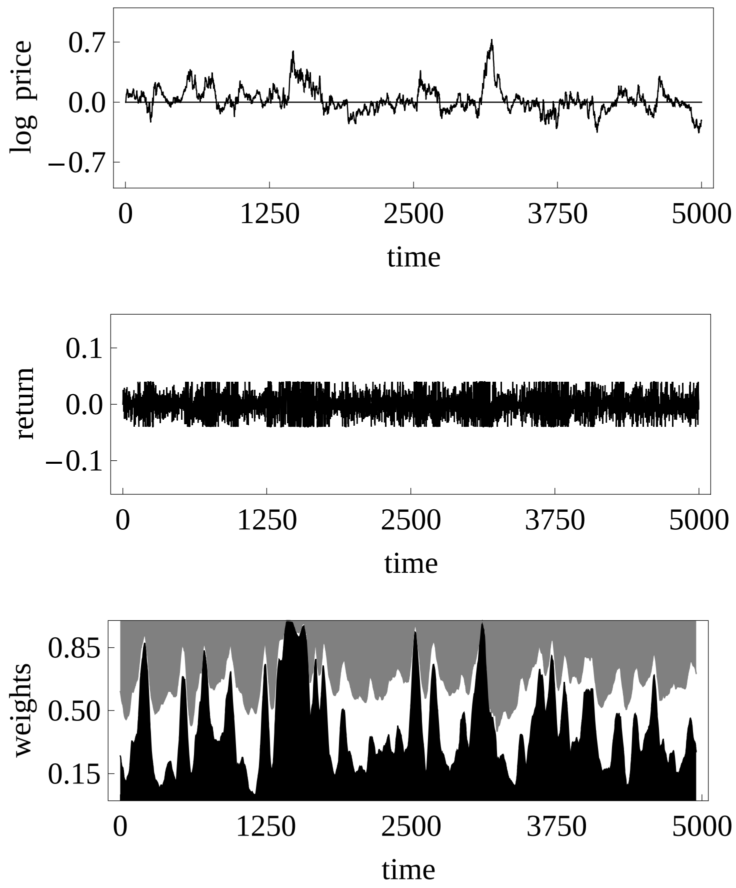


Figure 16: The dynamics of the model with trading halts in the time domain. Design and parameter setting as in figure 1 but $h = 0.04$.

Background

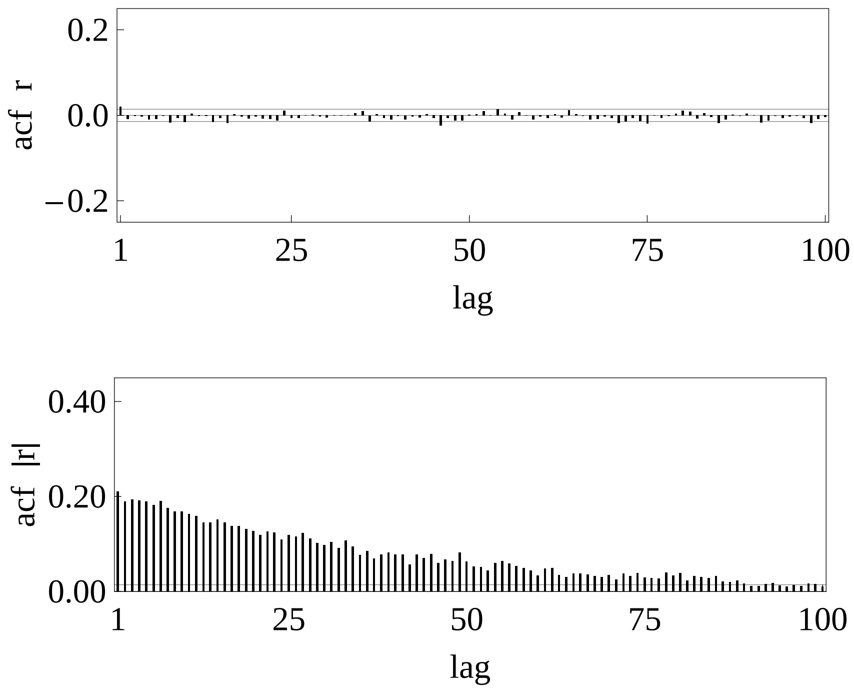


Figure 17: The autocorrelation functions for raw returns and absolute returns for the first 100 lags. Parameter setting as in figure 16, 20000 observations.

Results

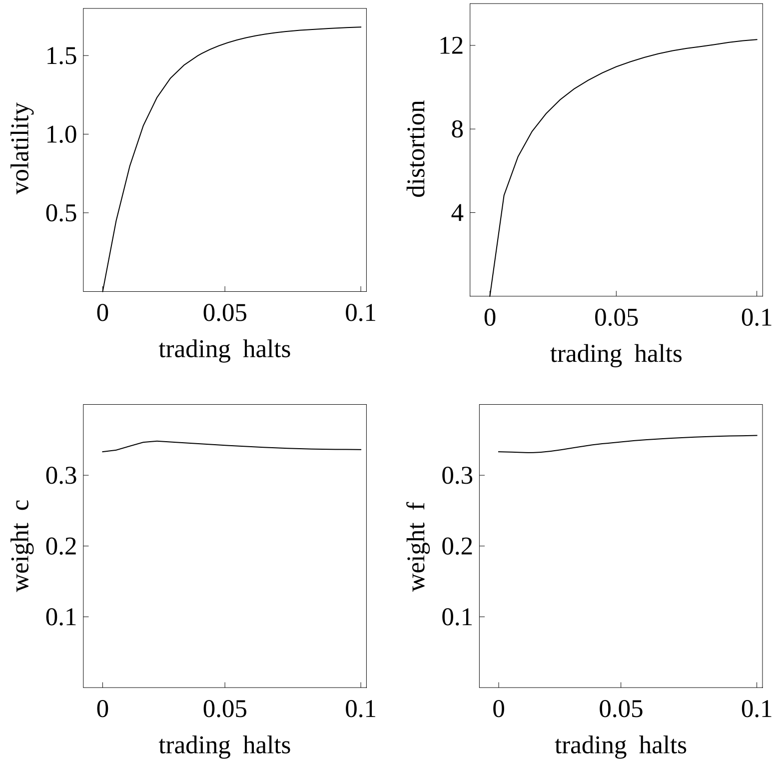


Figure 18: The impact of trading halts on the volatility (top left), distortion (top right), weight of technical traders (bottom left) and weight of fundamental traders (bottom right), respectively. Design and parameter setting as in figure 6 but h is varied between 0 and 0.1.

Robustness

Fundamental value

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

with $\eta \sim N(0, \sigma^{\eta})$

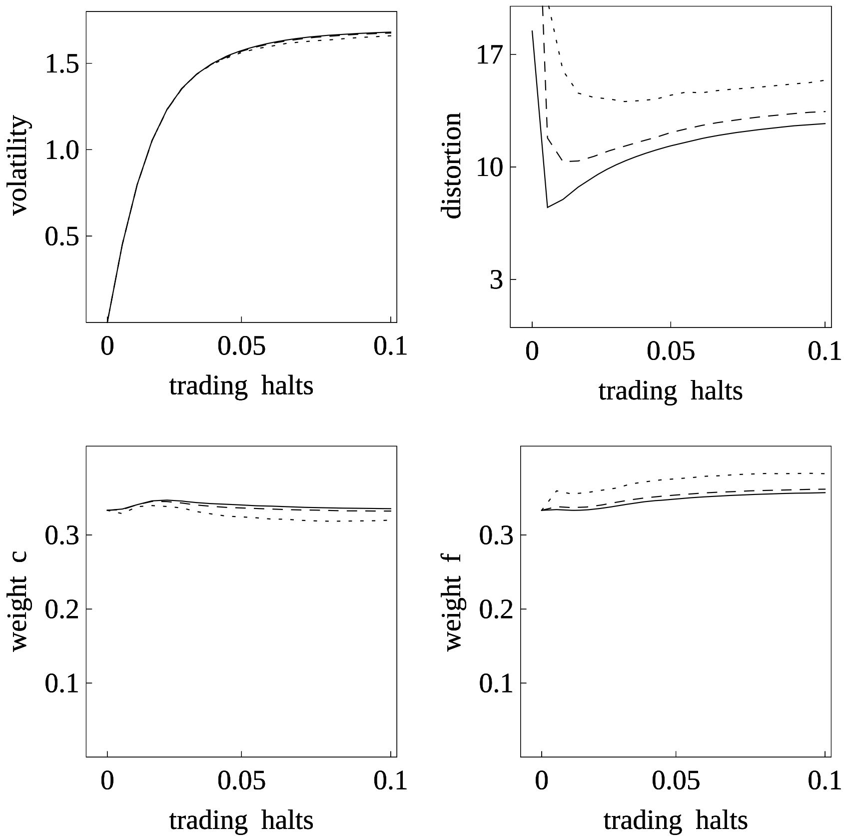


Figure 19: The impact of trading halts on volatility, distortion, weight of technical traders and weight of fundamental traders for different volatility levels of the fundamental value. Design and parameter setting as in figure 18 but $\sigma^{\eta} = 0.05$ (solid line), $\sigma^{\eta} = 0.1$ (dashed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

Conclusions

Some initial insights so far, mainly based on small scale models.

Analytical results are basically missing (use more simple models?) so far.

Robustness I: different small scale models.

Robustness II: more complicated models (artificial intelligence).

Laboratory experiments.

Potential for a huge research project.