

Disclosure Requirements, the Release of New Information and Market Efficiency: New Insights from Agent-based Models

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Abstract We explore how disclosure requirements that regulate the release of new information may affect the dynamics of financial markets. Our analysis is based on three agent-based financial market models that are able to produce realistic financial market dynamics. We discover that the average deviation between market prices and fundamental values increases if new information is released with a delay, while the average price volatility is virtually unaffected by such regulations. Interestingly, the tails of the distribution of returns become fatter if fundamental data is released less continuously, indicating an increase in financial market risk.

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1 Introduction

A key characteristic of financial markets is the recurring emergence of severe bubbles and crashes. During such turbulent market dynamics, public debate about a better regulation of financial markets usually flares up. However, the design of more stable financial markets is an intricate issue. For instance, empirical studies are often difficult to conduct since data to evaluate new policy regimes may simply be non-existent. Alternatively, realistic financial market models are required to stress test new policy measures.

Fortunately, such models have appeared recently in the form of agent-based financial market models. For surveys of this burgeoning field of research, see, for instance, LeBaron (2006), Chiarella et al. (2009), Hommes and Wagener (2009), Lux (2009) and Westerhoff (2009). In these models, boundedly rational traders rely on simple heuristic strategies, mainly technical and fundamental trading rules, to determine their investment positions. Simulations reveal that (nonlinear) interactions between heterogeneous market participants can create complicated asset price dynamics. Some of these models are even capable of producing artificial time series that have similar statistical features to actual financial market data (see, e.g. Chen et al. 2009). For instance, these models can generate bubbles and crashes, excess volatility, fat tails for the distribution of returns, uncorrelated price changes and volatility clustering.

A number of contributions have already been published where such models are used as computer platforms to evaluate certain policy measures. For instance, Westerhoff (2003) explored the consequences of trading halts, Scalas et al. (2005) insider trading and fraudulent behavior, He and Westerhoff (2005) price caps, Wieland and Westerhoff (2005) central bank interventions, Westerhoff and Dieci (2006) transaction taxes, Brock et al. (2009) hedging instruments, Hermsen (2010) Basel II regulations for market risk and Thurner et al. (2009) leverage effects. All in all, these approaches seem to enable us to improve our understanding of how certain regulatory policy measures function (for a survey, see Westerhoff 2008).

The focus of this paper is on disclosure requirements. One important aspect in the design of disclosure rules is how frequently firms should report new

information about their business condition to the general public.¹ For instance, should firms inform investors continuously or would it be better to inform them less frequently? An argument in favor of the first view could be that changes in the firms' fundamental values then emerge less abruptly. Moreover, the informational content of market prices may increase. Support for the second view could be based on the fact that good and bad new information may cancel each other out over time, making the evolution of the firm's fundamental values appear more stable. Also the information processing capabilities of market participants may be limited and a constant flow of new information may simply overburden them.

To explore the relationship between disclosure requirements, the release of new information and market efficiency, we use three different agent-based financial market models, namely the models of Lux and Marchesi (1999, 2000), Chiarella et al. (2006a, b) and Franke and Westerhoff (2009a, b). All these models are able to match, at least approximately, the stylized empirical facts of financial markets. We use the above models with the settings originally proposed. The only component we modify is the market participants' perception of the fundamental value. Our key conclusion is that market efficiency may benefit from a more continuous release of new information. In all three models we observe on average that prices are closer to fundamental values if investors are informed promptly about changes in a firm's economic performance. Although the price variability is virtually unaffected by this regulatory measure, financial market risk may nevertheless increase if new information becomes delayed. We find that the tails of the distribution of returns contain more probability mass in the event of a delayed release of new information. Put differently, the average price variability may remain constant but the distribution of returns changes such that more extreme price changes emerge. Given that extreme returns constitute a large part of financial market risk, policy makers may wish to prevent this. A (preliminary) policy recommendation is therefore that firms should disclose new information continuously.

¹ A recent example where this issue has controversially been discussed is the secret rescue of the RBS and HBOS by the Bank of England. Both banks received huge loans by the Bank of England in October and November 2008. However, these loans were made public only one year later in November 2009. The motivation for this "period of non-disclosure" was to prevent an immediate adverse impact on consumer confidence and a consecutive bank run (BBC 2009, The Economist 2009).

Our paper is organized as follows. In Section 2, we illustrate how disclosure requirements may affect the perception of fundamental values and introduce measures to capture market efficiency. In Section 3, we recall three agent-based financial market models and discuss their dynamics, both with an immediate and delayed update of fundamental values. In Section 4, we conduct a Monte Carlo analysis to systematically investigate the relation between disclosure requirements and market efficiency. The last section concludes.

2 Theoretical Background

Let us start with the theoretical background relevant to our analysis. In Section 2.1, we first introduce the concept of temporal information gaps and suggest how they can influence market efficiency. In section 2.2, we present a number of measures to evaluate market efficiency.

2.1 Temporal Information Gaps and Market Efficiency

The fact that information about the economic and financial conditions of firms is released only at discrete time steps produces what Witte (2009) terms temporal information gaps (TIGs). Technically speaking, a TIG can be defined as the time span from one period of publication of new information to the next. TIGs can cause market participants to be not up-to-date about a firm's true fundamental values, even if they are perfectly rational.

To capture the discrepancy between the true fundamental value and traders' perception of it, one can differentiate between the subjective fundamental value and the objective fundamental value. Under the assumption that new information appears randomly, the objective fundamental value, i.e. the true value, follows a random walk. The subjective fundamental value, i.e. traders' opinion about the true value, is constant as long as traders do not receive any new information. However, every time new information is published agents can – in principle – discover an asset's true value, such that the subjective fundamental value adapts to the objective one. The objective fundamental value then drifts away from the subjective one, until the next release of new information.

Figure 1 illustrates this behavior for a TIG of 63 periods, which corresponds approximately to a quarterly publication frequency. The objective fundamental value (dashed line) evolves in the form of a random walk (new information arrives every period and is normally distributed with mean zero and constant standard deviation). Every 63 periods, agents get to know the true value such that subjective fundamental values (solid line) and objective fundamental values correspond. Otherwise, the subjective value remains unchanged and starts to deviate from the true value.

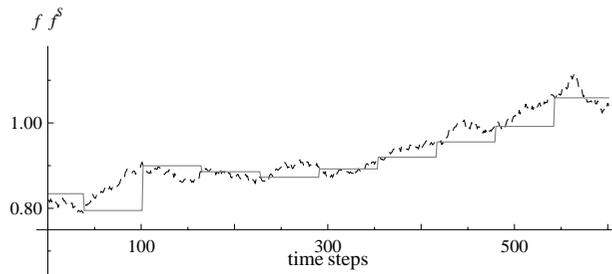


Figure 1: Relation between the objective and subjective fundamental value. The figure shows the evolution of the objective fundamental value (dashed line) and the subjective fundamental value (solid line) for a TIG of 63 days (approximately a quarter of a year).

In general, the relationship between TIGs and different indicators of market efficiency appears to be ambiguous. Firstly, longer TIGs obviously increase the discrepancy between the subjective and objective fundamental value. Therefore, longer TIGs can be expected to increase the deviation between market prices and objective fundamental values. Secondly, TIGs influence the overall noise level impacting on price dynamics, since every release of new information represents an exogenous shock for market participants. There are three important effects to consider.² Every quadruplication of the TIG quarters the number of shocks in a finite span of time (effect 1), doubles the average size of the shock once a shock

² We assume that the objective fundamental value follows a random walk. For a derivation of the quantitative relationships, see Witte (2009).

occurs (effect 2), and halves the average noise level, interpreted as the mean shock averaged over all periods (effect 3). These different effects influence the price dynamics. Nonetheless, the precise result is hard to foresee. Whereas effects 1 and 3 tend to stabilize market dynamics, effect 2 is presumably destabilizing. Due to these rival effects, we use agent-based models to explore the relationship between TIGs and market efficiency.

2.2 Measures of Market Efficiency

Considering relevant measures to characterize important aspects of financial market efficiency, we have to consider several aspects. On the one hand, prices should be close to fundamental values. On the other hand, price variability should be low. In particular, extreme price changes, which constitute a large part of financial market risk, should be rare.

Based on the distinction between the objective and subjective fundamental value, we can discriminate between two types of distortion. Objective distortion D^O captures the deviation of objective fundamental value f_t and market price p_t as follows:

$$D^O = \frac{1}{T} \sum_{t=1}^T |\ln p_t - \ln f_t|, \quad (1)$$

where T is the number of observations in a given sample. A higher objective distortion obviously indicates that the market prices contain less information about the asset's true fundamental value and that the market is less efficient.

The subjective distortion D^S takes the subjective fundamental value f_t^S into account. Hence,

$$D^S = \frac{1}{T} \sum_{t=1}^T |\ln p_t - \ln f_t^S|. \quad (2)$$

Subjective distortion measures the deviation from the market price and the subjective fundamental value, and may thus be regarded as the distortion perceived by market participants.

Let us define returns as the log price change, i.e. $r_t = \ln p_t - \ln p_{t-1}$. We can then measure volatility by the square root of the average return

$$V = \sqrt{\frac{1}{T} \sum_{t=1}^T r_t^2} . \quad (3)$$

An increase of V indicates an increase in the variability of prices and is thus an indicator of financial market risk.

As a second measure of financial market risk we consider the tail index of the distribution of returns. According to the Hill estimator (Lux and Ausloos 2002), this tail index can be calculated as follows. The absolute returns of a sample are first arranged in descending order $|r_L| > |r_{L-1}| > \dots > |r_{L-k}| > \dots > |r_1|$. The number of observations in the tail of the sample is denoted by k . The tail index is then obtained by

$$\alpha^H = \left(\frac{1}{k} \sum_{i=1}^k \ln(|r_{L-i+1}|) - \ln(|r_{L-k}|) \right)^{-1} . \quad (4)$$

Usual tail fractions are 2.5% and 5%. A lower α^H indicates more probability mass in the tails of the distribution of returns and thus the presence of more extreme returns. Contrary to the volatility measure (3), measure (4) thus focuses explicitly on extraordinary events.

3 Description and Dynamics of Models

We next present a brief informal outline of a number of relevant aspects regarding the models used in our study. For a detailed description, we refer to the respective literature. All the models considered are able to mimic important stylized facts of financial markets. At the moment it is not clear which of the three models replicates the statistical features of actual asset prices best. Another reason for using three different agent-based models is to check whether our main results display some robustness. A comprehensive survey of the potential of agent-based models to explain the stylized facts of financial markets is provided by Chen et al. (2009). Since we wish to explore the effects of temporal information gaps, we particularly focus on the implementation of the objective and subjective fundamental value.

3.1 Lux and Marchesi's Model

Lux and Marchesi's model (1999, 2000) contains a large number of interacting agents which fall into three groups: fundamentalists, optimistic chartists, and pessimistic chartists. The agents switch between these groups and, since this model is constructed in continuous time, they can do this several times a day. Profits are decisive for agents to switch between the groups of chartists and fundamentalists. Fundamentalists believe that the market price will revert to the fundamental value. The higher the discrepancy between the market price and fundamental value, the higher the expected profits of fundamentalism. Chartists extrapolate recent market price changes. Their actual profits are generated by short-term capital gains earned by price changes (or losses sustained by price falls). Fundamentalists' expected profits and chartists' actual profits are compared. They govern agents' switching behavior with respect to the two trading philosophies.

Whether a chartist is optimistic or pessimistic depends on two factors: the recent market price trend and the opinion index. This index measures the mood of the majority of chartists, thus taking into account herding behavior among agents. Both factors are combined in a function that determines switches from one group of chartists to the other. If both factors point in the same direction, such as a price increase together with a dominance of optimistic chartists, this is regarded as a strong indication of a continuing price increase. It is then likely that the number of optimistic chartists will increase. Price changes are realized by a market maker according to excess demand generated by traders (plus a normally distributed noise term).

The fundamental value in Lux and Marchesi (1999) is defined as a random walk. Its discrete time version reads

$$\log(f_{t+1}) = \log(f_t) + \sigma\varepsilon_t, \quad (5)$$

with $\varepsilon \sim N(0, 1)$. Here and in the following we regard one time step as one day.

Figure 2 gives an impression of the resulting dynamics.³ The left panels of Figure 2 provide a representative simulation run of the basic model. The top and middle panels show a price and return time series for 1200 days. Note that the market price tracks the objective fundamental value quite closely. Moreover, there are significant volatility outbursts (e.g. around time steps 1000). In periods of high volatility, we find a decrease in the fundamentalists' fraction (n_f) and an increase in the optimistic and pessimistic chartists' fractions (n_+ and n_-), as the bottom left panel shows. Put differently, an increase in the use of chartists' strategies causes an increase in volatility.

Instead of the objective fundamental value, in our experiments we use the subjective fundamental value f_t^S , defined as

$$f_t^S = \begin{cases} f_{t-1}^S, & \text{if } t \notin k \cdot TIG \\ f_t, & \text{if } t \in k \cdot TIG \end{cases}, \quad (6)$$

with $k \in \{1, 2, 3, \dots\}$ and $TIG \in \{1, 2, 5, 10, 15, 21, 25, 30, 63, 100, 250\}$. For any integer time step that is a multiple of a given TIG , the subjective fundamental value is updated to the objective fundamental value. For other time steps, the subjective fundamental value remains constant.

While the left panels of Figure 2 visualize aspects of the model with $TIG = 1$ (the fundamental value is updated on a daily basis and is thus perceived correctly), the right panels describe the dynamics of the model when new information is published quarterly ($TIG = 63$). Note that the market price is now close to the subjective fundamental value and may differ from the objective fundamental value. This is contrary to the basic model. As can also be seen, some of the extreme price movements occur simultaneously with the release of new infor-

³ Lux and Marchesi (2000) use four different parameter sets in their paper. We use their "set II", which is characterized as quite realistic concerning the stylized facts of financial markets. Similar results are obtained for other parameter sets. See also Alfarano and Lux (2007) for useful details about the simulation algorithm.

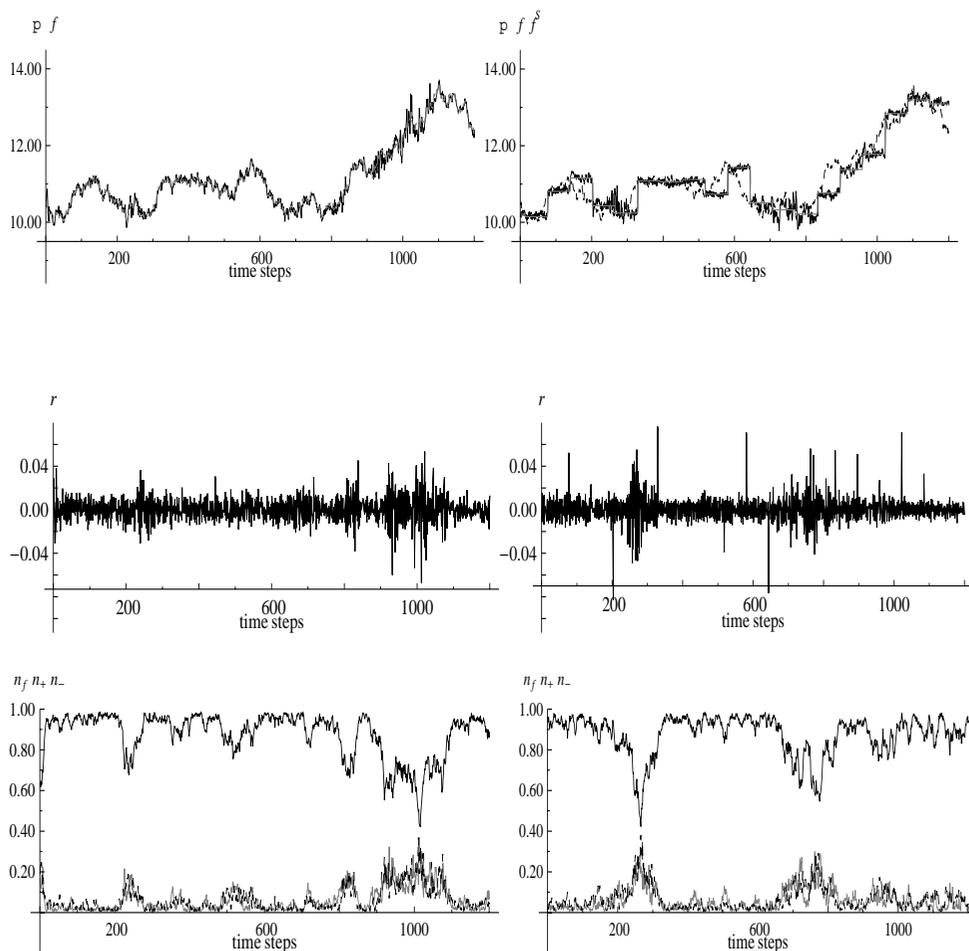


Figure 2: Dynamics of Lux and Marchesi's model. Left panels from top to bottom: the market price (black solid line) and the objective fundamental value (dashed line) for the basic model; returns; proportions of fundamentalists (black solid line), pessimistic chartists (gray solid line), and optimistic chartists (black dashed line). Right panels: identical to the left panels, albeit for a TIG of 63 days. The upper right panel also contains the subjective fundamental value (gray solid line).

mation.⁴ Note also that volatility outbursts appear at quite different periods, although we use the same seed of random variables in the two simulation runs. From inspecting individual time series it is thus hard to say whether different TIGs stabilize or destabilize financial market dynamics.

3.2 Chiarella, He and Hommes' Model

The asset pricing model of Chiarella, He and Hommes (2006a, b) is ruled by excess demand of a risky asset generated by fundamentalists' and chartists' trading rules. The more the market price is above (below) the fundamental value, the stronger the fundamentalists' intention to sell (buy) the risky asset, since they expect a price correction. The chartists' excess demand depends on a 100-day moving average rule (MA). If the market price is above (below) this MA, chartists buy (sell) the risky asset. The fractions of chartists and fundamentalists are modeled via a discrete choice model, where the corresponding fitness functions depend on realized net profits. A market maker changes prices with respect to the excess demand of chartists and fundamentalists. Moreover, the price adjustment is distorted by a normally distributed noise term.

The random walk of the fundamental value is modeled in Chiarella et al. (2006a)⁵ as

$$f_{t+1} = f_t(1 + \sigma\varepsilon_t), \quad (7)$$

with $\varepsilon \sim N(0,1)$. The subjective fundamental value f_t^S is again defined as in (6).

Figure 3 illustrates the dynamics for this model in the same way as Figure 2. Instead of the agents' fractions, we find, however, the excess demands of fundamentalists and chartists (d_f and d_c) in the bottom panels. The chartists'

⁴ The reason for this is as follows. If fundamentalists realize that the price of an asset has disconnected from its fundamental value, they place larger orders which, in turn, cause larger price adjustments.

⁵ We use the parameter setting given in Figure 3 of Chiarella et al. (2006a), since this setting is able to mimic the stylized facts of financial markets best.

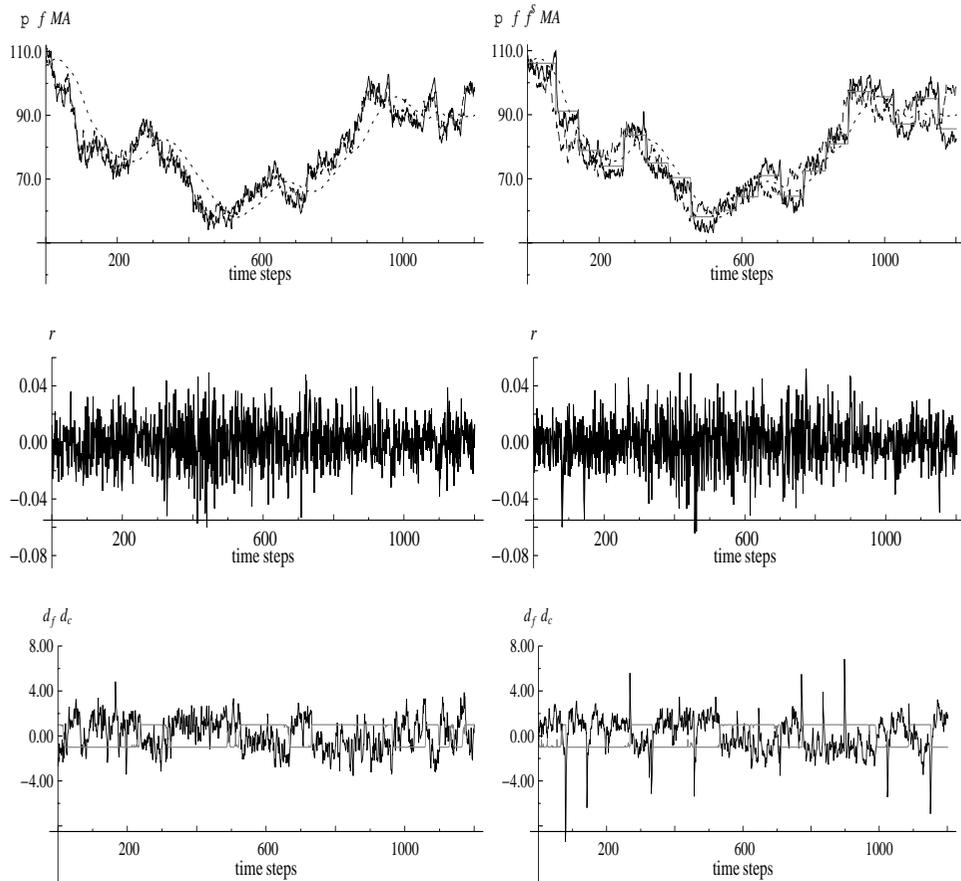


Figure 3: Dynamics of Chiarella, He and Hommes's model. Left panels from top to bottom: the market price (black solid line) and the objective fundamental value (dashed line), and 100 day moving average (dotted line) for the basic model; returns; excess demands of chartists (gray solid line) and fundamentalists (black solid line). Right panels: identical to the left panels, albeit for a TIG of 63 days. The upper right panel also contains the subjective fundamental value (gray solid line).

excess demand is positive if the 100-day MA is above the market price (and vice versa, of course). The fundamentalists' excess demand is more volatile, and a factor that causes extreme returns. In particular, the right bottom panel highlights this observation for the quarterly updated subjective fundamental value ($TIG = 63$). Strong price changes occur simultaneously with high absolute excess demand of fundamentalists at time periods when the fundamental value is revealed. Different price levels are one reason for the volatility cluster, as the top and middle panel both reveal. For lower price levels (time steps around 450), returns are on average higher than usual.

As already mentioned, the right panels of Figure 3 describe a situation for a quarterly updated fundamental value. Compared to the dynamics of the model by Lux and Marchesi (Figure 2), the market price is pushed away from both the objective and subjective fundamental value more strongly. However, the deviation between the market price and subjective fundamental value is still rather low compared to the deviation between the market price and objective fundamental value, and to our findings from the next model.

3.3 Franke and Westerhoff's Model

Franke and Westerhoff's model (2009a, b) contains two different groups of speculative traders: chartists and fundamentalists. Agents following fundamentalists' trading rules buy (sell) assets if the market price is below (above) the fundamental value; agents following chartists' trading rules extrapolate recent price trends. Both demand functions are buffeted by exogenous noise. A combination of predisposition towards chartism, herding effects and current market conditions is decisive for transitions between the two groups. The agents' herding behavior is formalized via a majority index x , which is bounded between -1 (all agents are chartists) and +1 (all agents are fundamentalists). The probability of a trader being a fundamentalist increases with the majority index and the observed distortion in the market. To be precise, the higher the fraction of fundamentalists and the higher the mispricing in the market, the greater the probability that an agent will use a fundamental trading rule. Finally, a market maker adjusts prices with respect to excess demand.

The fundamental value is assumed to be constant in this model. To investigate the effects of a deviation between the objective and subjective fundamental value,

we assume (5) for the fundamental value (instead of $\ln(f_{t+1}) = \ln(f_t)$, as defined in Franke and Westerhoff 2009a).⁶ The subjective fundamental value is given by (6).

Figure 4 is constructed analogously to Figures 2 and 3. As we can see, the model is able to replicate profound volatility clustering. Volatility outbreaks can be found around time step 400 for the basic model (left panels, daily update of objective fundamental value) or around time step 800 for the modified model (right panels, quarterly update of objective fundamental value). Volatility clusters occur simultaneously with a high proportion of agents following chartists' trading rules, as depicted in the bottom panels. Negative values for the majority index signal a dominance of chartism. For periods with a positive majority index, fundamentalists govern the dynamics, and volatility is lower.

Concerning the development of the market price and the objective fundamental value, the top left panel of Figure 4 ascertains that the deviation between the market price and fundamental value is already quite significant in the basic model. The top right panel indicates that this deviation does not change much if new information is revealed on a quarterly basis. This is a clear difference compared to the previous models, where we observe a higher deviation between market price and fundamental value compared to the basic model in the left panels, especially for $TIG=63$ (see Figures 2 and 3). Again, we observe that volatility outbursts occur in quite different periods for the selected TIGs.

4 A Monte Carlo Analysis

Now we systematically explore how different TIGs affect the dynamics of the agent-based models presented so far. In Section 4.1, we first clarify the simulation design. In Sections 4.2 to 4.4, we turn to a general analysis of the three models.

⁶ This requires a new assumption about the standard deviation of the news process. We take here the same value as in Lux and Marchesi (1999, 2000), i.e. we set the daily standard deviation to $\sigma = 0.005$. The other model parameters are as in Franke and Westerhoff (2009a, b).

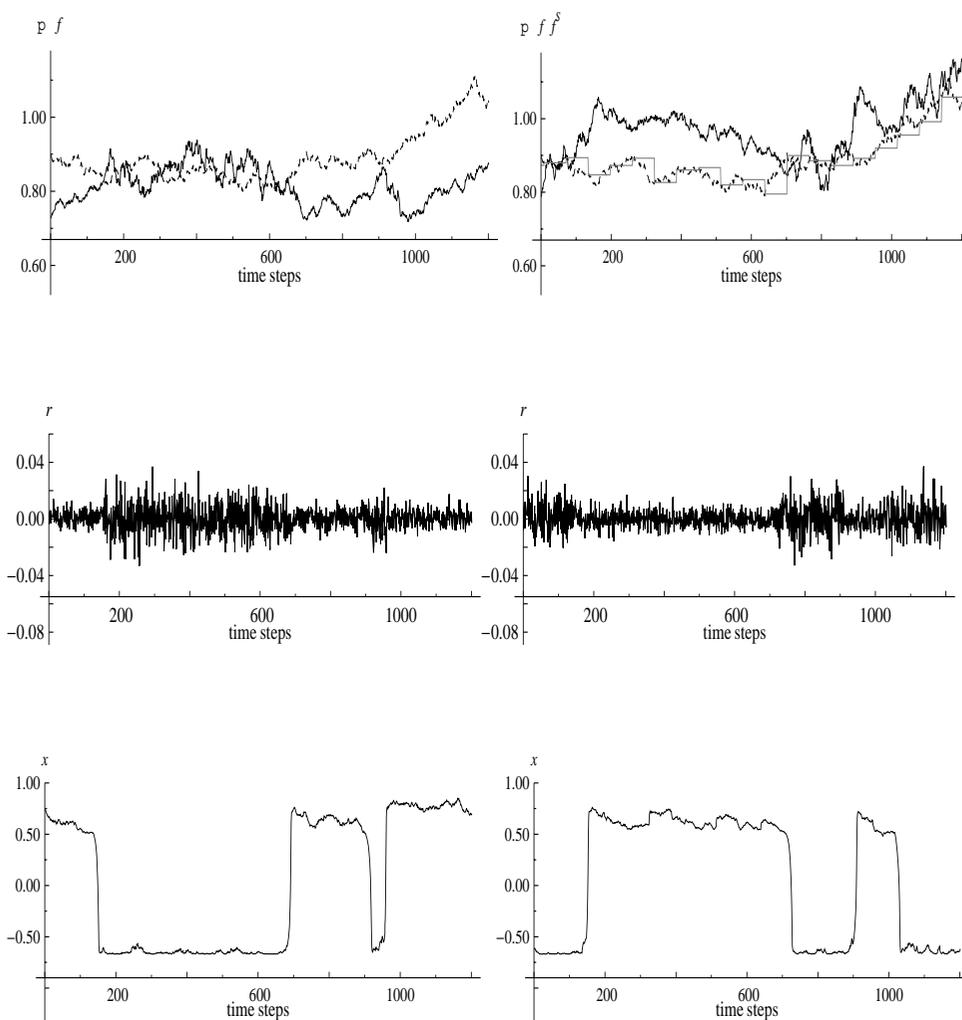


Figure 4: Dynamics of Franke and Westerhoff's model. Left panels from top to bottom: the market price (black solid line) and the objective fundamental value (dashed line) for the basic model; returns; development of the majority index ($x < 0$: majority of chartists; $x > 0$: majority of fundamentalists). Right panels: identical to the left panels, albeit for a TIG of 63 days. The upper right panel contains the subjective fundamental value (gray solid line).

4.1 Simulation Design

Our numerical results with respect to our four market efficiency measures are based on 500 time series (each with 5500 observations) for each TIG. For the TIGs, we choose 1 (daily publication), 2, 3, 4, 5 (weekly publication), 10, 15, 21 (monthly publication), 25, 30, 63 (quarterly publication), 100, and 250 (yearly publication). Figures 5 to 7 contain boxplots for the following market efficiency measures: objective distortion, subjective distortion, volatility, and tail index. Besides the 25% and 75% quantiles and the median, we also indicate the range of the minimum and maximum value for the 500 time series considered. Moreover, the black dots represent the means of the respective market efficiency measures.

4.2 Insights from Lux and Marchesi's Model

Figure 5 depicts the market efficiency measures for Lux and Marchesi's model. We do not observe any significant influence of the TIGs on volatility. On the other hand, the tail index changes considerably.⁷ For TIGs from 1 to 63 periods, the tail index declines steadily before rising again. Note that 63 periods correspond to a quarter of a year – the regular publication frequency applicable, for instance, to firms listed in the German stock market index DAX. Accordingly, the model suggests that the actual regular publication frequency in Germany produces the worst tails in the distribution of returns. The decline in the tail index for TIGs from 1 to 63 periods can be explained as follows. Extensive TIGs lead to large corrections of the subjective fundamental value, which, given that prices track fundamental values closely in this model, trigger large price movements. What causes the rise of the tail index for TIGs from 63 to 250 periods? As TIGs become extensive, corrections of the subjective value become seldom. Thus, heavy adaptive movements of prices occur less frequently.

⁷ Hence, return time series with “identical” volatility may nevertheless display different return dynamics. For instance, a return time series with more extreme returns may also have more lower returns so that the net effect on volatility is balanced.

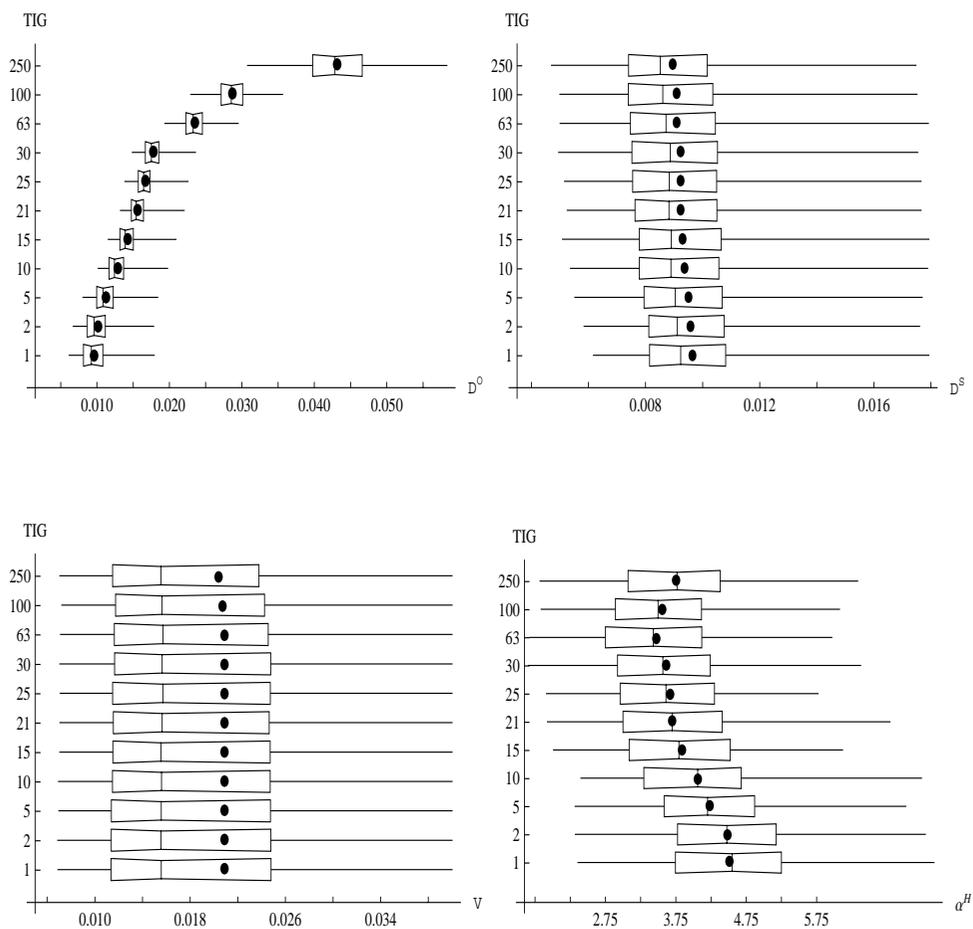


Figure 5: Market efficiency measures for Lux and Marchesi's model. Top left: objective distortion; top right: subjective distortion; bottom left: volatility; bottom right, tail index. The box of the box plots represents the 25% and 75% quantile, the horizontal line represents the range of the minimum and maximum of all 500 time series. The mid vertical line represents the median, whereas the black dot is the mean of the average volatility.

For the remaining measures we observe that TIGs have a negative effect on the objective distortion but do not influence the subjective distortion. This finding is in accordance with the insight that the discrepancy between the subjective and objective fundamental value tends to rise if TIGs increase. Market prices remain close to the subjective fundamental value but not to the objective one.

4.3 Insights from Chiarella, He and Hommes' Models

The efficiency measures for the model of Chiarella et al. are shown in Figure 6. Again, we do not observe any significant effect of TIGs on volatility. In contrast, the tail index decreases continuously, indicating longer TIGs to provoke heavy movements of prices. In comparison to Lux and Marchesi's model, the decline in the tail index is slightly smaller. The reason for this is that the dynamics of prices in the model of Chiarella et al. are less dependent on the evolution of the objective/subjective fundamental value than in Lux and Marchesi's model. Thus, corrections of the subjective fundamental value affect the dynamics of prices less directly. The distortion measures behave similarly to those in Lux and Marchesi's model: longer TIGs have a negative effect on objective distortion but do not significantly influence subjective distortion.

4.4 Insights from Franke and Westerhoff's Model

Results for Franke and Westerhoff's model are depicted in Figure 7. The model confirms the previous finding that TIGs do not influence volatility. However, when it comes to the tail index, the model reveals its special characteristic: in contrast to the previous models, there is no significant influence of TIGs on the occurrence of heavy returns. The reason for this is that in Franke and Westerhoff's model, the market price and fundamental value, irrespective of whether it is objective or subjective, evolve relatively independently of each other.⁸ Hence, the

⁸ Another prominent agent-based financial market model is that by Gaunersdorfer and Hommes (2007), which was modified and recalibrated recently by Franke (2009). In this Gaunersdorfer-Hommes-Franke model, prices may also significantly deviate from fundamental values. Results with respect to our four market efficiency measures for this model are quite similar to those observed for Franke and Westerhoff's model.

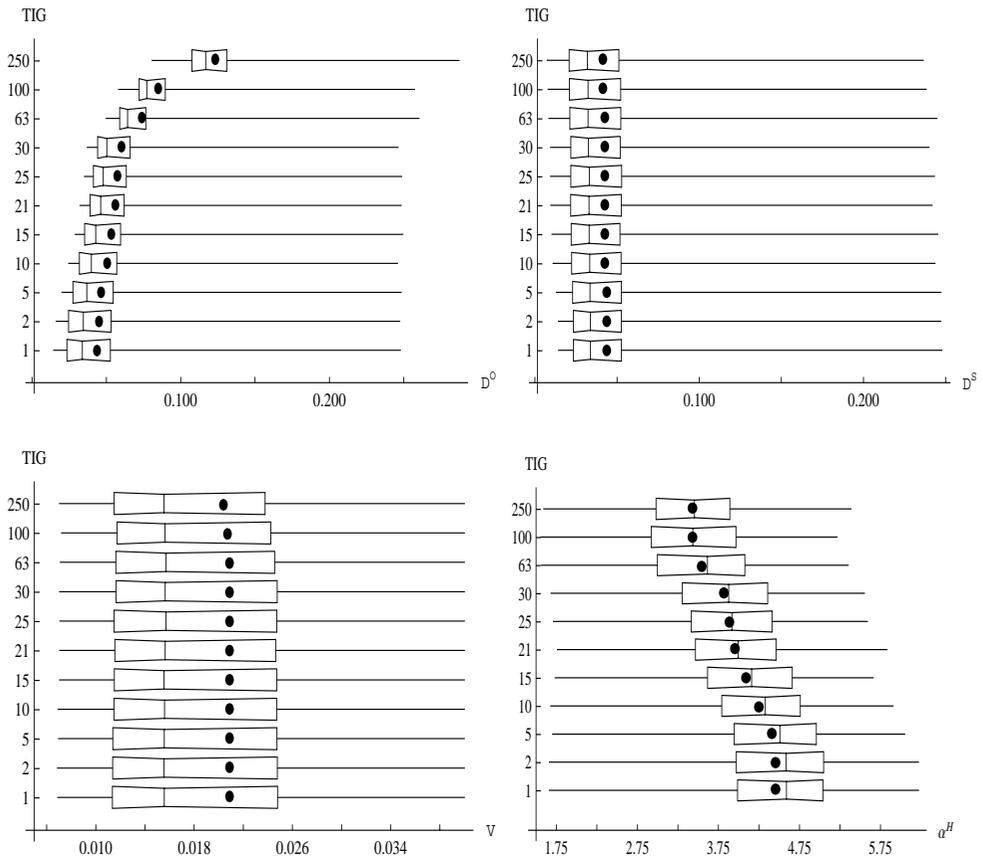


Figure 6: Market efficiency measures for Chiarella, He, and Hommes' model. The same design as in Figure 5, but volatility estimates are only depicted between 0.006 and 0.04

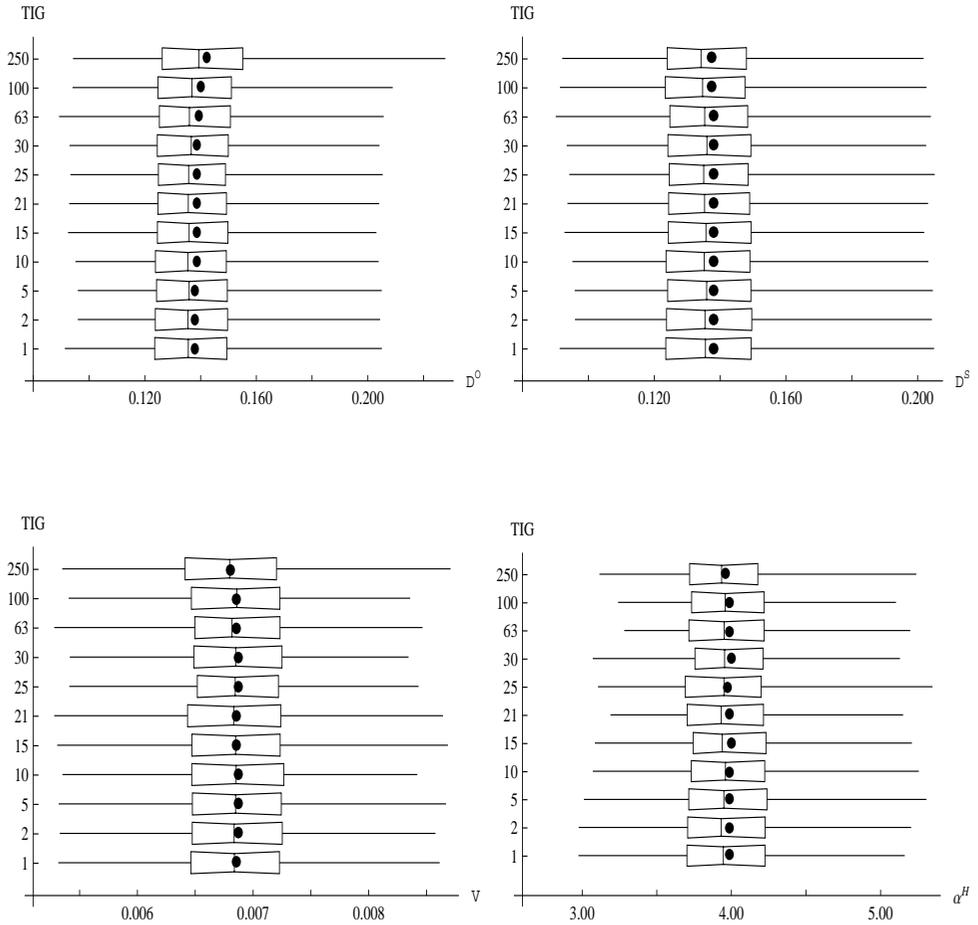


Figure 7: Market efficiency measures for Franke and Westerhoff's model. The same design as in Figure 5.

return distribution hardly changes, even if the corrections of subjective fundamental values become substantial. The individual characteristic of the model dynamics also becomes manifest in the distortion indicators. Compared to the other models, the effect of TIGs on objective distortion is relatively low. The reason for this is that in this model, average objective distortion is relatively large, even if new information is published instantly. Thus, TIGs cause only a relatively small part of the objective distortion. Regarding subjective distortion, the results of the other models are confirmed. There is no significant relation between TIGs and subjective distortion.

5 Conclusions

How should policy makers regulate firms' disclosure requirements with respect to the release dates of new information? To answer this question, we use three agent-based financial market models as a computational laboratory. All agent-based models are able to match the stylized facts of financial markets quite well, thus it seems reasonable to employ them in our study. The results we obtain from our Monte Carlo study can be summarized as follows:

- All models suggest that if firms release new information less frequently, the objective distortion increases, i.e. prices fluctuate, on average, more distantly towards their true fundamental values. This effect is more pronounced in models in which prices track their fundamental values more closely.
- In the eyes of market participants, the average perceived deviation between prices and fundamental values, that is the subjective distortion, is more or less constant across different temporal information gaps. This result is confirmed by all three models.
- Different publication frequencies appear to have virtually no impact on volatility. We find that for low, medium and high temporal information gaps, the variability of prices remains essentially constant.
- The latter observation does not, however, imply that financial market risk also remains unaffected. Interestingly, we find that the tail index of the distribution of returns may decrease if the length of the temporal information gap increases. In particular, in the Lux-Marchesi model the probability of extreme

returns is maximized if firms release information on a quarterly basis. The effect of the temporal information gap depends on how closely market prices track subjective fundamental values. If market prices are more disconnected from perceived fundamental values, this effect is rather weak. However, if market prices are close to perceived fundamental values, as we would expect in efficient markets, this effect becomes significant.

All in all, we conclude from our experiments that firms should instantly give clear and precise information about their economic performance, at least with respect to market efficiency.

Of course, this policy recommendation should be viewed with caution. Our approach may be extended in various directions to check the robustness of our findings:

- A central question is how traders perceive fundamental values in reality. Here we assume that they are able to compute the objective fundamental value once they have all of the relevant information. In reality, however, this may not be true. For instance, traders may use different heuristics to calculate the fundamental value, and thus there may even be coexisting perceptions of fundamental values among market participants.
- Moreover, traders may try to form expectations about the arrival of new information. Suppose that the fundamental value has increased in the recent past. Traders may then believe that this trend will continue, even if fundamental values follow a random walk.
- If a greater length of time elapses between publication dates, market participants may also become nervous because uncertainty regarding the true fundamental value will increase. On the other hand, the amount of information market participants have to process increases if firms continuously inform about their economic conditions.
- We followed the literature and assume that the (objective) fundamental value changes every time step. However, this variable may also be modeled as a Poisson jump process.
- Our attention is on a market with a single risky asset. It would be interesting to see how the dynamics work in a model with multiple assets. Should all firms inform the public about new information simultaneously?
- Note that we take only one dimension of disclosure requirements into account, namely the frequency of news releases. Other dimensions such as the level or

the style of disclosure requirements play, of course, also an important role for market stability and may have significant impacts on the firms' financing and investment decisions (see Admati and Pfleiderer 2000, Boot and Thakor 2001, Holmström and Kaplan 2003 and Östberg 2006, among others).

All these aspects reveal that much more work is needed to arrive at a solid policy recommendation. Our paper may be regarded as a start in this direction. Nevertheless, we believe that agent-based financial market models may be used to improve our understanding of how new information should be released. Here we learn that it may be better for market efficiency if firms inform the market about their economic situations continuously.

References

- Admati, A.R. and Pfleiderer, P.C. (2000): [Forcing firms to talk: financial disclosure regulation and externalities](#). *Review of Financial Studies* 13 (2): 479-519.
- Alfarano S. and Lux T. (2007): [A noise trader model as a generator of apparent financial power laws and long memory](#). *Macroeconomic Dynamics* 11 (S1): 80-101.
- Boot, A.W.A. and Thakor, A.V. (2001): [The many faces of information disclosure](#). *Review of Financial Studies* 14 (4): 1021-1057.
- BBC (2009): [Secret bank rescue loans revealed](#). BBC News, 2009/11/24.
- Brock, W., Hommes, C. and Wagener, F. (2009): [More hedging instruments may destabilize markets](#). *Journal of Economic Dynamics and Control* 33 (11): 1912-1928.
- Chen, S.-H., Chang, C.L. and Du, Y.-R. (2009): Agent-based economic models and econometrics. *Knowledge Engineering Review*, in press.
- Chiarella C., He X.-Z. and Hommes C. (2006a): [Moving average rules as a source of market instability](#). *Physica A* 370: 12-17.
- Chiarella C., He X.-Z. and Hommes C. (2006b): [A dynamic analysis of moving average rules](#). *Journal of Economic Dynamics and Control* 30 (9-10): 1729-1753.
- Chiarella, C., Dieci, R. and He, X.-Z. (2009): Heterogeneity, market mechanisms, and asset price dynamics. In: Hens, T. and Schenk-Hoppé, K.R. (eds.): [Handbook of financial markets: dynamics and evolution](#). Amsterdam: North-Holland: 277-344.
- Franke, R. (2009): On the specification of noise in two agent-based asset pricing models. Working Paper, University of Kiel.

- Franke, R. and Westerhoff, F. (2009a): [Validation of a structural stochastic volatility model of asset pricing](#). Working Paper, Universities of Bamberg and Kiel.
- Franke, R. and Westerhoff, F. (2009b): [Estimation of a structural stochastic volatility model of asset pricing](#). Working Paper, Universities of Bamberg and Kiel.
- Gaunersdorfer, A. and Hommes, C. (2007): A nonlinear structural model for volatility clustering. In Teyssière, G. and Kirman, A. (eds.): [Long memory in economics](#). Berlin: Springer, 265-288.
- He, X.-Z. and Westerhoff, F. (2005): [Commodity markets, price limiters and speculative price dynamics](#). Journal of Economics Dynamics and Control 29 (9): 1577-1596.
- Hermesen O. (2010): [Does Basel II destabilize financial markets? An agent-based financial market perspective](#). European Physical Journal B 73 (1): 29-40.
- Holmström, B. and Kaplan, S. (2003): [The state of US corporate governance: what's right and what's wrong?](#) Journal of Applied Corporate Finance 15 (3): 8-20.
- Hommes, C. and Wagener, F. (2009): Complex evolutionary systems in behavioral finance. In: Hens, T. and Schenk-Hoppé, K.R. (eds.): [Handbook of financial markets: dynamics and evolution](#). Amsterdam: North-Holland: 217-276.
- LeBaron, B. (2006): Agent-based computational finance. In: Tesfatsion, L. and Judd, K. (eds.): [Handbook of computational economics: agent-based computational economics](#). Amsterdam: North-Holland: 1187-1233.
- Lux T. and Marchesi M. (1999): [Scaling and criticality in a stochastic multi-agent model of a financial market](#). Nature 397: 498-500.
- Lux T. and Marchesi M. (2000): [Volatility clustering in financial markets: a microsimulation of interacting agents](#). International Journal of Theoretical and Applied Finance 3 (4): 675-702.

- 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](#). Berlin: Springer: 373-410.
- Lux, T. (2009): Stochastic behavioural asset-pricing models and the stylize facts. In: Hens, T. and Schenk-Hoppé, K.R. (eds.): [Handbook of financial markets: dynamics and evolution](#). Amsterdam: North-Holland: 161-216.
- Östberg, P. (2006): [Disclosure, investment and regulation](#). Journal of Financial Intermediation: 15 (3): 285-306.
- Scalas, E., Cincotti, S., Dose, C. and Raberto, M. (2005): Fraudulent agents in an artificial financial market. In Lux, T., Reitz, S. and Samanidou, E. (eds.): [Nonlinear dynamics and heterogeneous interacting agents](#). Berlin: Springer: 317-326.
- The Economist (2009): [Bigger than you thought](#). 2009/11/26.
- Turner, S., [Farmer](#), D. and Geanakoplos, J. (2009): [Leverage causes fat tails and clustered volatility](#). Working paper, arXiv:0908.1555.
- Westerhoff, F. (2003): [Speculative markets and the effectiveness of price limits](#). Journal of Economic Dynamics and Control 28 (3): 493-508.
- Westerhoff, F. (2008): [The use of agent-based financial market models to test the effectiveness of regulatory policies](#). Jahrbücher für Nationalökonomie und Statistik (Journal of Economics and Statistics) 228: 195–227.
- Westerhoff, F. (2009): Exchange rate dynamics: a nonlinear survey. In: Rosser, J.B., Jr. (ed): [Handbook of research on complexity](#). Cheltenham: Edward Elgar: 287-325.
- Wieland, C. and Westerhoff, F. (2005): [Exchange rate dynamics, central bank intervention and chaos control methods](#). Journal of Economics Behavior and

Organization: 58 (1): 117-132.

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 (2): 293-322.

Witte, B.-C. (2009): [Temporal information gaps and market efficiency: a dynamic behavioral analysis](#). BERG Working Paper No. 64, University of Bamberg.

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