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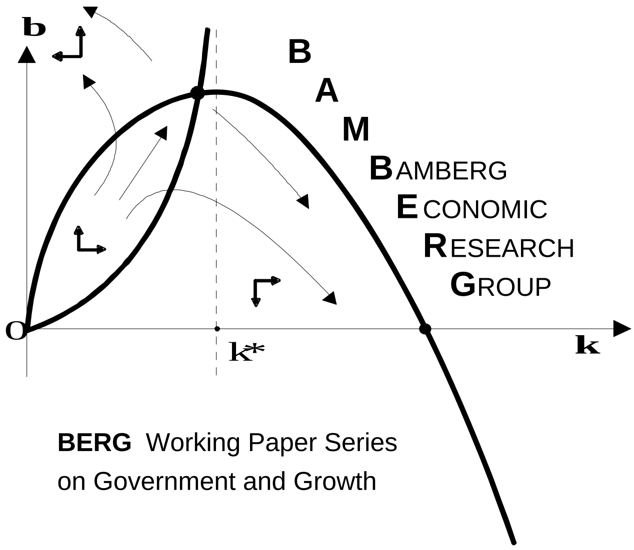

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Temporal information gaps and market efficiency: a dynamic behavioral analysis

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Abstract: This study seeks to explore, how market efficiency changes, if ordinary traders receive fundamental news more or less often. We show that longer temporal information gaps lead to fewer but larger shocks and a reduction of the average noise level on the dynamics. The consequences of these effects for market efficiency are ambiguous. Longer temporal information gaps can deteriorate or improve market efficiency. The concrete result depends on the stability of the market together with the interval in which the length of the gap is incremented.

Keywords: Temporal information gaps, market efficiency, disclosure policy, agent-based financial market models, technical and fundamental analysis.

JEL classification: G12; G14.

1. INTRODUCTION

Conceived in the 1960s the Efficient Market Hypothesis (EMH) has become one of the most famous economic paradigms. It states that security prices fully reflect all available fundamental information. Fama (1970) has differentiated three interpretations of such efficiency. The following formulation rests partly on Jensen (1978):

> In general a market is efficient with respect to information set θ_t if θ_t is properly reflected in prices.
>
> – In the weak form θ_t comprises solely the information contained in the past price history of the market as of time *t*.
>
> – In the semistrong form θ_t comprises all information publicly available at time *t*.
>
> – In the strong form θ_t comprises all information known to anyone at time *t*.

In the past thirty years lots of empirical (e.g. Shiller 1981, Cutler et al. 1989, Lev 1989, Mitchel and Mulherin 1994) as well as some analytical findings (Grossmann and Stieglitz 1980, Shleifer and Vishny 1997) have challenged the EMH. The flourishing field of behavioral finance (see, e.g. Shleifer 2000, Hirshleifer 2001, Shiller 2003, or Lo 2004) has proposed some explanations of its failing. The central insight is that agents do not process information fully rationally but follow sentiments and commit systematic errors. Still, this view simplifies the reality of financial markets. Due to publicity laws and corporate disclosure policies, for instance, traders do not even receive fundamental information currently. Our analysis focuses on this fact and its consequences for market efficiency.

The underlying question of our research is: How does market efficiency change, if ordinary traders receive fundamental information more or less often? In this context, the term “temporal information gap” will denote the span of time in which traders do not receive any fundamental news. For the purpose of a deeper classification of the research problem let us conceptualize the process of value discovery as a complex process. The computation of the proper fundamental value necessities three conditions:

I. Fundamental data must be available. In reality disclosure regulations obligate firms to disseminate fundamental data only at discrete steps of time.

II. Fundamental data must be complete, correct and definite. In reality disclosure regulations do not prescribe to publish all value-relevant information and give considerable leeway to creative accounting.

III. Agents must know the exact relationship between fundamental information and value. Not every real trader is an expert and uses rational methods to compute the true value out of the bulk of data. Additionally, the methods themselves are diverse and approximative.[1]

-------- Figure 1 --------

Figure 1 illustrates the process of value discovery. The process implicates the possibility of information gaps on the side of traders. The term "information gap" is originated in agency theory where it is used synonymously for the deficit of information of the agent relative to the principal. Regarding the process of value discovery two causes of such an information deficit become apparent. First, agents have not received the latest information and second, agents have received the latest information, but the information lack of content. Accordingly, we denominate the first form of information gap as "temporal" and the second as "substantive". Temporal as well as substantive information gaps can arise in various extents. The extent of a temporal information gap (TIG) is determined by the time that agents lack of current information. We specify the TIG as the number of periods in which agents do not get any

[1] For an overview of common methods see Brealey et al. (2006).

news. At the end of a TIG, e.g. via corporate disclosure, agents receive all information. We assume that once the information is public, the true fundamental value is known to traders, that is, condition II and III are fulfilled.[2]

To conduct our analyses we construct an agent-based model of a financial security market. The chartist-fundamentalist approach has proven to be a powerful tool in this area (for recent surveys see Hommes 2006, LeBaron 2006, Lux 2006, Westerhoff 2008 and Westerhoff 2009. The behavioral approach is based on the observation that financial traders use two main strategies: fundamental and technical analysis. Fundamentalists fix their orders to economic fundamentals, whereas chartists try to predict prices by simple technical trading rules based upon patterns in past prices, such as trends. The interplay of both strategies creates model dynamics that replicate some stylized facts of real financial markets.

What might be a reasonable assumption about the relationship of TIGs and market efficiency? Consider that the forces of arbitrage tend to adjust prices to the value which arbitrageurs assume to be proper. TIGs make possible that this estimation is already misaligned in reference to the true fundamental value. Clearly, the misalignment tends to be heavier, the less often arbitrageurs receive fundamental information, i.e., the longer the TIG. One may conclude that longer TIGs should lead to a fall of market efficiency, at least in the strong form. Market efficiency in the semistrong form might not be influenced by TIGs, since the concept merely measures the difference between true prices and arbitrageurs' subjective fundamental perception while ignoring the objective misalignment of the latter.

The results of our study run counter to these intuitions. Longer TIGs do not always mean a fall of market efficiency. The explanation lies in the complex effects of TIGs on price

[2] One may wonder why we do not simply speak of information lags instead of temporal information gaps. The reason is that the term "information lag" suggests that all information is disclosed with the same delay. This does not apply to our model since we assume information of different periods to be released in a bundle.

volatility. We observe that under certain circumstances longer TIGs tranquilize market dynamics, which in turn improves efficiency. Thus, even if longer TIGs increase the bias between the true fundamental value and the perception of traders, market efficiency, in each form, improves if the volatility effect is strong enough. The analysis will show that the overall effect of larger TIGs on market efficiency depends on the endogenous stability of the market and on the interval in which the TIG is incremented.

The paper is organized as follows: Section two is dedicated to a deeper theoretical foundation of our project. We recapitulate the state of efficiency research and conceptualize the process of value discovery. Section three derives the relationships between TIGs and the noise affecting the market. In section four we introduce the chartist-fundamentalist approach and develop a dynamic behavioral model accordingly. Section five presents the model simulations, resumes the complex results, and intends to provide interpretations. Section six underscores the relevance of the results in the context of corporate disclosure policy and institutional regulation. Finally, in section 7 we summarize the most important findings.

2. TEMPORAL INFORMAION GAPS AND NOISE

This section is dedicated to TIGs, noise and the relationship between both. Economics refer to noise in many contexts and use the term with different connotations.[3] In the context of our study we define noise as an exogenously driven influence on the dynamics of prices. Shocks are understood as singular occurrences of noise.

In general, exogenous influences on the dynamics of prices arise from changes of the fundamental data. If fundamentals change, traders will compute a new fundamental value, reformulate their orders respectively, and prices will adjust to the new demand. Clearly, this

[3] Black (1986) provides an overview of different fields and senses in which noise affects market efficiency.

mechanism requires that traders are informed about the occurrence which has shifted fundamentals. As long as fundamental movements are not communicated to traders, they will not manipulate the dynamics of prices. During the TIG, therefore, no shocks will appear. This observation enables us to specify the initial definition of shocks: Shocks consist in the recognition of fundamental changes from one observation step to another. Let the parameter gap denote the length of a TIG. It follows that a shock will arise every gap^{th} period. Formally:

$$t_{shock} = n * gap; \qquad n = 1,2, \ldots N, \tag{1}$$

where t_{shock} is any period in which a shock affects the dynamics of prices.

What can be said about the relationship between *gap* and the average "size" of the shocks? If the true fundamental price follows a random walk, it will tend to drift apart from an initial value over time. Accordingly, as long as traders are not informed about fundamental movements, the deviance between their subjective pricing of the fundamental value and its true level tends to rise. Thus, when traders finally learn the relevant data, the perceived change of the fundamental value will on average be heavier, the longer the preceding TIG. We conclude that the shocks on price dynamics will be stronger, the higher the gap.

The exact quantitative relationship is easy to derive. Assume that the evolution of the fundamental value (F) is defined by

$$F_{t+1} = F_t + R_t; \qquad R_t \sim N(0, \sigma^2), \tag{2}$$

where R_t is the change of fundamentals in period t. R_t is a normally distributed, independent variable with mean 0 and variance σ^2. For the normal distribution holds that if X and Y are independent normal random variables with $X \sim N(\mu_X, {\sigma_X}^2)$ and $Y \sim N(\mu_Y, {\sigma_Y}^2)$, then their sum U is normally distributed with $U = X + Y \sim \mathrm{N}(\mu_X + \mu_Y, {\sigma_X}^2 + {\sigma_Y}^2)$.

It follows that if $R_1, R_2, \ldots, R_n$ are independent normal random variables with $R_1 \sim N(0, \sigma^2)$, $R_2 \sim N(0, \sigma^2)$, …, and $R_n \sim N(0, \sigma^2)$, then their sum S is normally distributed with $S = \sum_i^n R_i \sim \mathrm{N}(0, n\sigma^2)$.

This means that if traders learn the fundamental value every gap^{th} period, the variance of the perceived changes, and therefore the size of the shocks, will be gap-times the variance of the periodical change of fundamentals. Formally:

$$\sigma_{shock}{}^2 = gap * \sigma^2, \tag{3}$$

where $\sigma_{shock}{}^2$ is the variance of shocks. Since the mean noise equals zero, the variance σ^2 is computed by

$$\sigma^2 = E[R^2], \tag{4}$$

where $E[R^2]$ is the expected value of the squared fundamental changes. From (3) and (4) for we thus derive:

$$\sigma_{shock}{}^2 = gap * E[R^2], \tag{5}$$

Let R_{shock} denote the occurrences of shocks, then due to (5) the following relationship must be valid:

$$\sigma_{shock}{}^2 = E[R_{shock}{}^2], \qquad \text{with } R_{shock} = \sqrt{gap} * R. \tag{6}$$

From (6) results:

$$\phi R_{shock} = \sqrt{gap} * \phi R, \tag{7}$$

where ϕR_{shock} is the average absolute shock and ϕR the average absolute periodical change of fundamentals. Accordingly, the average size of the shock after gap periods of zero fundamental news received by the traders will be $\sqrt{gap}$-times the average periodical change of fundamentals.

In summary, we could detect two effects of TIGs on noise:

A. The higher the TIG, the less often shocks hit the dynamics of prices.

B. The higher the TIG, the heavier the shocks will be.

As exogenous shocks are generally known to destabilize dynamics, the two effects must be rivaling: When TIGs grow, the effect of fewer shocks (A) tends to stabilize the dynamics, whereas the effect of heavier shocks (B) works destabilizing.

Which of the two effects prevails with respect to the average noise level? We define the average noise level as the mean shock averaged over all transaction periods, no matter if a shock appears or not. Formally:

$$\phi R_{noise} = \phi R_{shock} / gap. \quad (8)$$

Clearly, if traders correctly perceive fundamentals in every period, all fundamental movements will be transferred into reactions of demand and prices somehow. This is different if traders learn the true fundamentals every gap^{th} period, with $gap > 1$. Probably, if gap is high, not all fundamental changes in the span of gap periods push fundamentals in the same direction. When traders finally learn the true fundamental value, movements will have offset each other to some degree. The sum of changes which are actually transferred into formulations of demand and prices will be lower than the sum of changes in total. The extent to which fundamental occurrences compensate each other tends to rise, the less often the relevant information is available and fewer changes will be transferred into shocks. Therefore, the average noise level declines when incrementing the TIG. Note that the compensationeffect is also the cause, why by (7) a higher TIG raises the mean size of the shocks only under proportionally.

From (7) together with (8) the exact relationship between gap and the average noise level can be deduced as:

$$\phi R_{noise} = \frac{1}{\sqrt{gap}} * \emptyset R, \qquad (9)$$

Let us summarize our findings in a pragmatic form:

Every quadruplication of the TIG will…

- …quarter the number of shocks in a finite span of time by (1).
- …double the mean size of the shock by (7).
- …halve the average noise level by (9).

We conclude that the consequences of TIGs for price dynamics are ambiguous. TIGs lead to fewer shocks but enlarge them. The result that the average noise level is reduced suggests that TIGs might stabilize market dynamics. However, the further analysis will show that this idea is sometimes wrong.

3. THE MODEL

3.1. Motivation

The notion of price adjustment and value discovery as complex processes call for a dynamic analysis. The psychological aspects of value discovery implicate a behavioral view. Drawn together the project demands a dynamic behavioral approach. The chartist-fundamentalist approach (CFA) matches these needs. The CFA is a specification of the agent-based modeling approach, targeting the exploration of financial market dynamics.

Models with heterogeneous agents have proven to be quite successful in the past and have sharpened our understanding of the dynamics of real financial market. Agent-based modeling rests on the well supported evidence that individuals are boundedly rational (Simon 1955, Kahneman, Slovic and Tversky 1986, Smith 1991). In order to find orientation and to compensate their lack of knowledge agents rely on heuristics, that is, behavioral rules. This is also true for agents in financial markets. A broad stock of empirical evidence agrees that investors apply either fundamental or technical trading rules (e.g. Taylor and Allen 1992, Menkhoff 1997, Lui and Mole 1998). The CFA reproduces the generic ideas of the two strategies: Fundamentalists trade on fundamental information. They evaluate economic, industrial, and corporate conditions in order to estimate the value of an asset as the present value of the expected future dividends. Fundamentalists expect prices to return to value sooner or later. Consequentially, they try to exploit mispricing. The strategy aims at long-run profits (Graham and Dodd 1951, Greenwald et al. 2001). In contrast, chartists trade with the trend. They regard past price movements as an indicator of the market sentiment. Consequentially, chartists extrapolate price trends. The strategy aims at short run returns (Edwards and Magee 1966, Pring 1991, Murphy 1999).

CFA-models displaying the interaction of both agent groups can create complex nonlinear dynamics. Some of these models replicate the stylized facts of real financial markets quite adequately. Among those facts are: bubbles and crashes, excessive volatility (variations of price that cannot be justified by fundamental news), non-normal distributed returns, and volatility clustering (alternation of periods of low and high volatility).[4]

With reference to the market dynamics each group of investors plays a different role. The effect of fundamentalism is comparable with arbitrage. The strategy leads to a reduction of the

[4] For a deeper study of stylized facts see Mantenga and Stanley (2000), Cont (2001), Lux and Ausloos (2002), Johnson, Jefferies and Hui (2003) or Sornette (2003).

mispricing adding a negative feedback to the dynamics. The extrapolation of price trends by chartist brings a positive feedback and produces market inefficiency.

The model-driven CFA affords several methodical advantages. The method enables to precisely gauge all variables, control for exogenous shocks and generate as much data as needed.

3.2. Setup

The model we use here may be regarded as a extension of the model developed in Westerhoff (2003a). The Setup can be summarized as follows: We look at a stylized speculative market of financial securities. Traders can switch between technical and fundamental strategy. For every period the fraction of traders relying on each trading rule depends on the current distortion of the market. Every gap periods agents update their cognition of the fundamental value. After having chosen a strategy agents formulate their orders accordingly. The resulting excess demand generates the price of the next period at last.

In our model we differentiate two conceptualizations of the fundamental value: the objective and the subjective one. The objective fundamental value refers to the price omniscient and perfectly rational agents would compute as the proper security price. In this sense the objective fundamental value equals the true fundamental value. We assume insiders to have such a view. Contrarily, the subjective fundamental value corresponds to the imperfect perception of traders who are affected by temporal information gaps.

In order to model the objective fundamental value we keep up the general assumption for the evolution of fundamentals made in (2). Let F^O denote the objective fundamental value, then:

$$F_{t+1}^O = F_t^O + R_t; \qquad R_t \sim N(0, \sigma^2), \tag{10}$$

R_t still denotes the change of fundamentals in period t, since every new fundamental occurrence will instantly effectuate an adequate adjustment of the objective fundamental value.

In order to model the subjective fundamental value we assume that ordinary traders correctly compute the true fundamental value once they learn all relevant information. Contrarily, when no news reaches investors, they will base their calculations on the most recent data. Remember that traders receive fundamentals every *gap* periods. We formalize:

$$F_{t+1}^S = \begin{cases} F_{t+1}^0, \ t+1 \in \{gap, 2gap, \ldots, Ngap\} \\ F_t^S, \ otherwise \end{cases} \tag{11}$$

Equation (11) states that the subjective fundamental value equals the objective fundamental value every gap^{th} period, as to all these steps traders catch up their information deficit. In all other periods the subjective fundamental value of tomorrow remains the same as today, since traders reckon up the same old numbers.

Let us turn to the inner working of the market. The price adjustment process is given by a so-called price impact function (Farmer and Joshi 2002). A price impact function relates today's excess demand for an asset to the change of the price from today to tomorrow. The excess demand equals the sum of the individual demands of chartists and fundamentalists weighted with their relative fraction in the market. Accordingly, the security price *S* in period *t+1* is given by

$$S_{t+1} = S_t + a^M (W_t D_t^C + (1 - W_t) D_t^F), \tag{12}$$

where D_t^C and D_t^F stand for the demand of chartists and fundamentalist respectively, and W_t denotes the relative fraction of chartists. a^M is a positive price adjustment coefficient. According to (12), excess buying drives prices up, whereas excess selling drives prices down.

The higher a^M, the stronger the reaction of prices will be. The equation is a simplification of the actual order matching mechanism. It may be interpreted as a stylized description of the behavior of risk-neutral market makers who adjust prices with respect to excess demand.

The demand of chartist can be written as

$$D_t^C = a^C(S_t - S_{t-1}), \tag{13}$$

with the positive parameter a^C regulating the aggressiveness of chartists. Chartists bet on the latest price trend to go on. Hence, they receive a buying (selling) signal if the current price exceeds (undercuts) the price level one period before.

The orders generated by the fundamental strategy can be expressed as

$$D_t^F = a^F(F_t^S - S_t), \tag{14}$$

where a^F calibrates the strategy's aggressiveness. Fundamentalists believe that prices tend to revert to the fundamental value. Therefore, they get a buying (selling) signal, if prices are above (below) the fundamental value. Since traders do not always know the true fundamental value, the subjective fundamental value is relevant here.

Finally we formalize the weight of chartist as:

$$W_t = \frac{1}{1+b^1+b^2\left(F_t^S - S_t\right)^2} \tag{15}$$

The equation represents the switching mechanism of traders between technical and fundamental strategies. The more prices deviate from value, the more traders adhere to fundamental analysis. The arguments of Black (1986) and Hommes (2001) support the intuition. According to Black trading on information (i.e. fundamentalism) instead of noise (i.e. chartism) promises more profits to exploit, the higher the distortion of prices. Hommes argues that if prices deviate strongly from the fundamental value a consolidation is probable.

Fundamental trading rules prescribing to trade against the bubble become attractive. In contrast, technical strategies which rely on the bubble's growing inflation become risky. b^1 and b^2 (15) are positive parameters regulating the quantitative dimension of the bell-shaped function. The higher b^1, the greater the proportion of traders who never desist from fundamental trading. The higher b^2 the faster traders switch to fundamentalism when prices disconnect from fundamentals. Again, the perceived subjective fundamental value is important here.

3.3. Calibration

Taylor and Allen (1992) report that 5 to 10 percent of traders always stick to fundamental analysis. b^1 = 0.1 is consistent with this finding. $b^2$is set to 100. We choose a^M = 1 and a^F = 2. The reaction-coefficient left to configure is a^C. Westerhoff (2003b) indicates that the interaction of traders might reproduce some of the stylized facts of financial markets purely endogenously. Accordingly, we choose a^C such that the model yields complex dynamics even with constant fundamentals $(\sigma = 0)$. This applies for a^C in the range of 2 to 8. In the following simulations we will vary a^C within these restrictions in order to carry out the analysis under different market conditions. Depending on the simulation run we will set σ to 0 or 0.2.

4. SIMULATIONS

4.1 Capturing Efficiency

The model we have built allows testing for all three forms of market efficiency. We concentrate on the semistrong and the strong form. We measure market efficiency in terms of volatility and distortion. We define volatility as the average of absolute returns, that is:

$$\varnothing V = \frac{1}{n}\sum_{t=1}^{n}|S_t - S_{t-1}| \tag{16}$$

Relative to volatility, distortion captures market efficiency more directly. We define distortion as the average absolute deviation of prices from its fundamental value. Since our analysis distinguishes objective and subjective fundamentals we come to two versions of distortion. The first version is:

$$\varnothing D^O = \frac{1}{n}\sum_{t=1}^{n}|S_t - F_t^O| \tag{17}$$

The formalization gives the average absolute deviation of prices from objective fundamentals. As the objective fundamental value represents the insider view, the equation directly yields a measure of market efficiency in the strong from. The second version is:

$$\varnothing D^S = \frac{1}{n}\sum_{t=1}^{n}|S_t - F_t^S| \tag{18}$$

The formalization gives the average absolute deviation of prices from subjective fundamentals. Since the subjective value accounts for the information publicly available, the equation directly yields a measure of efficiency in the semistrong form.

4.2 Some numerical results

The tools just developed enable us to evaluate the simulation runs presented in this section. For every run a legend on the right displays the measures of volatility ($\varnothing V$) as well as subjective ($\varnothing D^S$) and objective distortion ($\varnothing D^O$).

We first want to get a feeling for the endogenous dynamics of the model. By setting τ to zero F^O remains constant to 100 over time. Accordingly, no noise will disturb the dynamics. Figure 2 shows the evolution of prices for two different values of a^C. In the first run a^C

equals 2, in the second a^C has been altered to 8. Remember that a^C represents the reaction intensity of chartists.

-------- Figure 2 --------

Watch the upper simulation run first. The dynamic of prices follows a rather complex walk neither reaching an equilibrium state nor a regular attractor. Considering the absence of fundamental news the volatility of 0.44 must be completely excessive. Furthermore, the dynamics switches between intervals of calm (e.g. from t = 225 to t = 275) and turbulent (e.g. from t = 80 to t = 160) motion. This phenomenon is known as on-off intermittency. On-off intermittency is a form of volatility clustering which is produced completely endogenously. For the objective fundamental value being constant over time there is no TIG in the cognition of traders. The subjective and the objective fundamental value coincide. As a result, objective and subjective distortion are equal ($\emptyset D^S$ = $\emptyset D^O$ = 0.27). In general, our model replicates some of the stylized facts of real financial markets.

Now contemplate the run below. Remember that the chartist strategy is calibrated to be more aggressive. We observe that the volatility of the dynamics has risen remarkably. This is true for intervals of low and high volatility. Furthermore, on-off intermittency has become distinctive. From time to time and without apparent reason the dynamic jumps into a phase of extreme fluctuations. In the following the oscillations decline gradually and finally settle down to the normal level. Overall, the average volatility has climbed to 3.67. Moreover, the higher volatility has caused an increase in distortion. Subjective and objective distortions have reached at 1.87. In general, the higher intensity of chartism has deteriorated market efficiency considerably. The observation holds for efficiency in its strong and in its semistrong form.

For the following analyses we set σ to 0.2. The objective fundamental value now moves in every transaction period. This is a necessary condition for the study of TIGs. For TIGs greater than one period ordinary traders will have an information deficit relative to insiders.

Figure 3 resumes the results for a^C = 2. The length of the TIG has been varied. The first three panels show exemplary simulation runs for different gaps. For every run the curve of prices together with the curve of objective fundamentals are drawn. The two panels on the bottom aggregate the results of several simulations.

-------- Figure 3 --------

In the first simulation run *gap* equals one period. Accordingly there is no TIG. The subjective value equals the objective one. Objective and subjective distortion correspond. For the fundamentals now follow a random walk, the level of prices changes over time.[5] Moreover, intervals in which prices strongly fluctuate around the subjective value (e.g. from t = 170 to t = 230) alternate with periods in which prices follow value rather accurately (e.g. from t = 230 to t = 330). Relative to the respective simulation run with no noise (Figure 1, first panel) volatility and distortions have risen significantly.

What part of the volatility can be attributed to shifts of fundamentals? In our model σ = 0.2 is equivalent to an average periodical change of the objective value of about 0.16. With 1.39 the measured price volatility is excessively higher. We conclude that the vast majority of price volatility points to true market inefficiency. The measures of distortion confirm the fall of efficiency. Objective and subjective distortion have climbed to 0.72. Evidently, efficiency has deteriorated due to the presence of noise.

In the second simulation run *gap* has been increased to twenty periods. Recall that, the demand of traders is based on subjective fundamentals, However, the longer the TIGs, the more the objective value, following a random walk, tends to drift apart from the subjective

[5] We cannot see the curve of objective fundamentals because it is covered by the evolution of prices.

one. Hence, trading is geared to a level which continuously less corresponds to the true fundamental value. As a result, we expect objective distortion to rise.

Indeed, prices start to disconnect from objective fundamentals. Furthermore, we observe that when traders get to know the latest information, their subsequent reaction sometimes entails phases in which volatility is relatively high (e.g. at t = 180). Overall, the average volatility has dropped to 0.87. As a result, the subjective distortion has also declined to 0.49. Moreover, the objective distortion has remained constant to 0.72. This observation strongly contradicts our intuition just established. The solution is that we have ignored the effect of volatility on distortion. Even if prices fluctuate around a less adequate value, due to lower oscillations the objective distortion has not risen.

In the third run *gap* has been increased another time to 160. The disconnection of prices from objective fundamentals has become unmistakable and more durable than before. When traders now get the latest information, their reaction can be drastic. The consequent trading on the news pushes the dynamics into quite long lasting phases in which volatility is pronounced. Apparently, news is not instantly transformed into a new level of prices but initiate a complex adjustment process. Within the phase of adjustment trading volume is high since agents interact intensively. Fundamentalists directly react to the fundamental news and induce a price trend towards the new fundamental value. Unfortunately, chartists trade on this trend and provoke an overshoot. When the misalignment is too heavy, chartism withdraws and fundamentalism takes control again. The mechanism repeats until prices have settled down to their normal attractor. However, the true fundamental value has considerably shifted in the meantime. The dynamics is swinging into a level that does not represent the true fundamental value anymore. Obviously, the adjustment process is too slow to guarantee market efficiency, neither in the strong, nor in the semistrong form. On the contrary, arbitrage itself has yield inefficiency by stimulating intense trading volumes and excessive volatility. The efficiency measures reflect the observations. As a result of the turbulent phases, the overall volatility has escalated to 1.55. Because of the higher volatility the subjective distortion has increased to 0.81. Due to the rise of volatility and due to the higher divergence between subjective and objective fundamentals the objective distortion has climbed to 2.02.

The two panels at the bottom confirm the results for a large number of observations. Watch the left bottom panel first. The panel shows the relationship between different TIGs and volatility. We measured volatility for gaps of 1, 10, 20, 40, 80, and 160 periods. For every gap we performed 20 runs of 5000 periods and computed the average volatility. The high number of observations should guarantee that the results are not disturbed by chance. The curve reveals a decline of volatility at the beginning. However, for gaps greater than 20 the volatility increases continuously.

The panel on the right captures the respective measures of objective (dashed curve) and subjective distortion. For small gaps both curves fall indicating lower distortion. For higher gaps the graphs slope upwards; objective and subjective distortion rise. Note that the subjective distortion is solely affected by price volatility. Thus, both curves are alike. Apart from volatility, the rising inadequacy of subjective value consequent to higher TIGs shapes the curve of objective distortion. As a result, for every gap the objective distortion lies above the subjective one.

We now turn to the case of aggressive chartists setting a^C to 8. Figure 4 illustrates the results. The organization of the panels and the underlying methods of computation are the same as before. Since the dynamics of prices would cover the curve of fundamentals completely, we let the latter apart.

-------- Figure 4 --------

Let us inspect the topmost simulation run first. Relative to the runs before the measures of volatilities and, therefore, distortions have exploded. Additionally, the effects of higher TIGs have changed. Altering the gap from 1 to 40 has boosted volatility and distortions. Obviously, this is because the dynamics tends jump into phases of exceeding volatility when traders receive the latest fundamentals after a while of no news at all. However, when we increase the gap further to 160, volatility and distortions decline. The cause is that the number of phases of immense volatility has dropped.

The panels on the bottom mirror the observations. For small gaps volatility and distortions grow, whereas for larger gaps they shrink.[6] Since for all gaps volatility is high in comparison to the change of fundamentals, the volatility effect on objective distortion is highly dominant. As a consequence the curves of subjective and objective are both shaped by volatility leading to similar evolutions of all three graphs.

In comparison with the case of $a^C = 2$ the curves of volatility and distortions have reverted. Apparently, the endogenous stability of the market, determined by the aggressiveness of chartists, dictates the relationship between TIGs and market efficiency.

Figure 5 merges the results. We have measured volatility, subjective, and objective distortion for different combination of TIGs and parameter a^C. The panels reveal smooth transitions from the level curves for a $a^C = 2$ (front side) to the level curves of $a^C = 8$ (back side). The regularity of the relationships can be confirmed.

-------- Figure 5 --------

[6] Clearly, with respect to objective distortion this cannot be the end of the story. If traders would not achieve any information about the true fundamentals (i.e. the gap tends infinity), prices would not follow objective fundamentals at all; objective distortion is maximal.

4.3 Interpretation

What are the reasons for the different relationships between market efficiency and the length of the TIG? The answer lies in the effects of TIGs on the noise impacting the dynamics. As demonstrated in section 2, longer gaps lead to fewer shocks (A), but heavier shocks (B). The positive consequences of effect A are rather linear; the less often shocks disturb the dynamic, the more often the dynamics follows its natural run. In contrast, the negative consequences of effect B depend on the endogenous characteristics of the market.

If the market is endogenously quite stable (a^C = 2), it can compensate a certain size of shocks relatively well. As a result, for small gaps the positive effect A dominates effect B; the average volatility declines. However, from a certain gap length on the market cannot withstand the shocks anymore and phases of strong volatility appear. Effect B dominates effect A; the average volatility rises.

In the instable configuration (a^C = 8) the market is very sensitive to noise because chartists aggressively extrapolate the adjustment reaction of fundamentalists subsequent to news. Hence, even small shocks can trigger phases of huge volatility. As a result, the negative consequences of effect B are remarkable from short gaps on; average volatility rises. Nonetheless, incrementing the gap beyond a certain level does not produce additional volatility. The cause is that once the shocks are continuously heavy enough to initiate high volatility phases, effect A starts to prevail: shocks become fewer and, thus, fewer phases of high volatility show up; the overall volatility declines.

Market efficiency in the semistrong form, that is, subjective distortion results directly from market volatility. Hence, longer gaps can deteriorate or improve semistrong market efficiency. Market efficiency in the strong form, that is, objective distortion results from volatility and from the bias between subjective and objective value. The bias between perceived and true value tends to rise with larger gaps. Accordingly, we expect strong efficiency to fall. However, if longer gaps simultaneously stabilize the dynamics, the change in volatility sometimes offsets the intuitive relation. We observe this phenomenon especially when the market is endogenously highly unstable (a^C = 8). Hence, under certain circumstances longer TIGs improve market efficiency, even in the strong form.

We conclude that the impact of temporal information gaps on market efficiency is ambiguous. Both, strong and semistrong efficiency can rise or fall with larger TIGs. The exact result depends, first, on the endogenous characteristics of the market and, second, on the interval in which we increment the gap.

The observations may be interesting but still do not satisfy. Are the effects of temporary information gaps on market efficiency indeed so intricate? In our model the complexity of the findings is due to the ability of the model to produce turbulent phases in response to shocks of a certain size. The occurrence of phases of abnormal volatility consequent to singular exogenous shocks is denoted as transient behavior. Is transient behavior a property of real financial markets? Indeed, there is much empirical evidence which documents that the variability of stock returns after annual and interim earnings announcements is abnormal high (e.g. Beaver 1968, May 1971). Transient behavior can be found in reality.

5. RELEVANCE

We suppose the results to offer some new insights for theory and practice. Up to now, research seems to believe that a reduction of the information asymmetry between ordinary traders and firms, without a doubt, would improve market efficiency (e.g. Lev 1992). Our dynamic analysis could prove that this relation does not hold necessarily.

In practice private as well as public institutions could benefit from these results. First, the findings are relevant for corporate information disclosure strategy[7]. Several studies report that firms disseminate good news more often than bad news (e.g. Pastena and Ronen 1979, Kross and Schroeder 1984, Dye and Sridhar 1995). In general, firms have been observed to voluntarily disclose value-relevant information quite rarely. We assume that firms are interested in keeping the volatility of its stock prices low in order to achieve high calculability and suggest stability to the public. If so, holding back information may be risky. Suppose that with the next regular report the withheld information come out all together. Then, the batch of news reaching traders could push the dynamics of prices in a phase of high volatility.

Second, disclosure regulation setters may regard the results with respect to market distortion as a direct indicator of market efficiency. The common belief is that strict disclosure requirements warrant liquid and efficient markets and reduce the cost of capital for firms. Admati and Pfleiderer (2000) prove that a tightening of disclosure regulations can be welfare beneficial. However, it may be difficult to identify the precise regulation to exploit the positive potential. Moreover, there are cases in which stronger regulation is harmful since corporate costs of disclosure exceed the public benefit. Our analysis confirms and amplifies the findings. “Forcing firms to talk” more often may be efficiency-, and thus, welfare-improving, yet sometimes welfare shrinks. The conclusion holds beyond disclosure costs.

6. CONCLUSION

Our study has demonstrated that the effects of temporal information gaps on market efficiency are far from straightforward. While we supposed longer temporal information gaps to deteriorate market efficiency, the analysis has shown that the relationship may sometimes be the other way around. The simulations have demonstrated this for market efficiency in the

[7] For a survey of corporate disclosure strategy see Lev (1992).

semistrong and in the strong form. The surprising results could be explained by the relationships between temporal information gaps and the noise affecting the dynamics. Extensive gaps lead to fewer but heavier shocks. Overall the average noise level declines. The changes in noise influence market volatility. Subjective market distortion (semistrong market efficiency) directly results from volatility. The relationship between information gaps and objective market distortion (strong market efficiency) is determined by volatility and by the discrepancy between subjective perception and true fundamental value. If average volatility declines consequent to an extension of the temporal information gap, the negative effect of the increased perception bias is sometimes offset. As a result, market efficiency, even in its strong form, may improve when the temporal information gap is prolonged. The abnormal finding is especially likely, if retaining news tranquilizes market volatility relatively well.

In general, our study supports the notion of price adjustment and value discovery as complex processes. While the configuration of value discovery represented the depended variable, the complexity of the adjustment process turned out to arise endogenously by the presence of different trading strategies. We could observe that arbitrage implicates the intense interaction of traders over a certain span of time. During the phase of adjustment the market can be highly volatile. In this sense the mechanism of arbitrage itself may temporarily trigger, instead of removing, inefficiency.

We believe that there is still need for investigation on the topic. While our model driven approach contributed to uncover the complex aspects of the relationship between temporal information gaps and market efficiency, future research should identify how likely the different scenarios might be for reality. We hope our study will motivate successive projects in this area.

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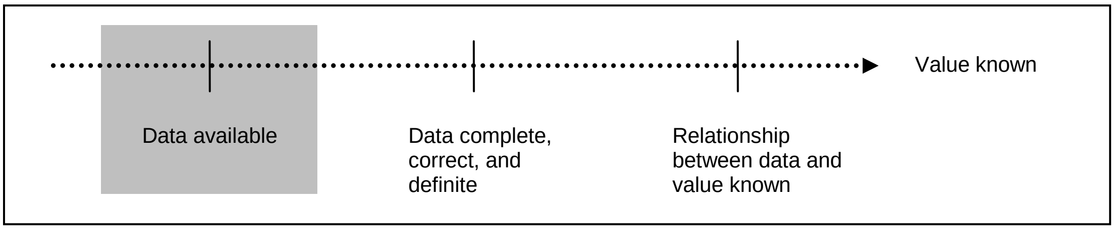

Figure 1: Discovery of fundamental value as a complex process

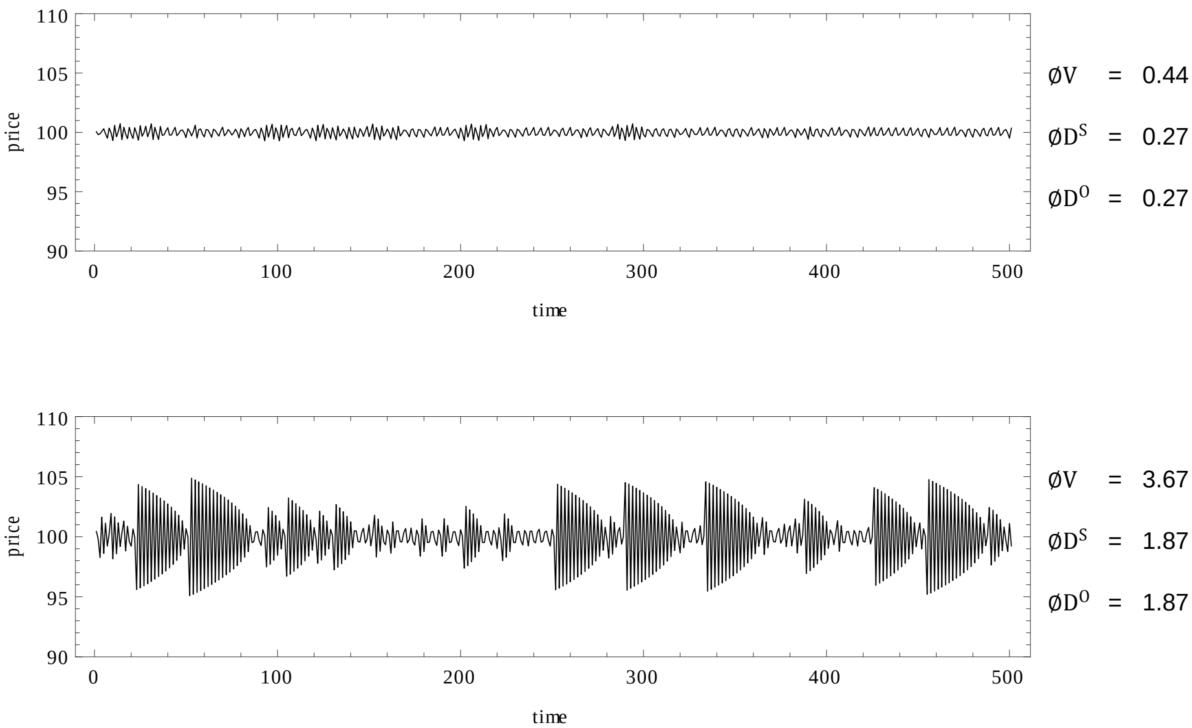

Figure 2: The panels show the dynamics of prices for different values of a^C, the reaction parameter of chartists. In the first panel a^C = 2, in the second a^C = 8. Volatility (ØV) and distortions ($ØD^O$, $ØD^S$) of the respective simulation run are appended on the right. No noise was added.

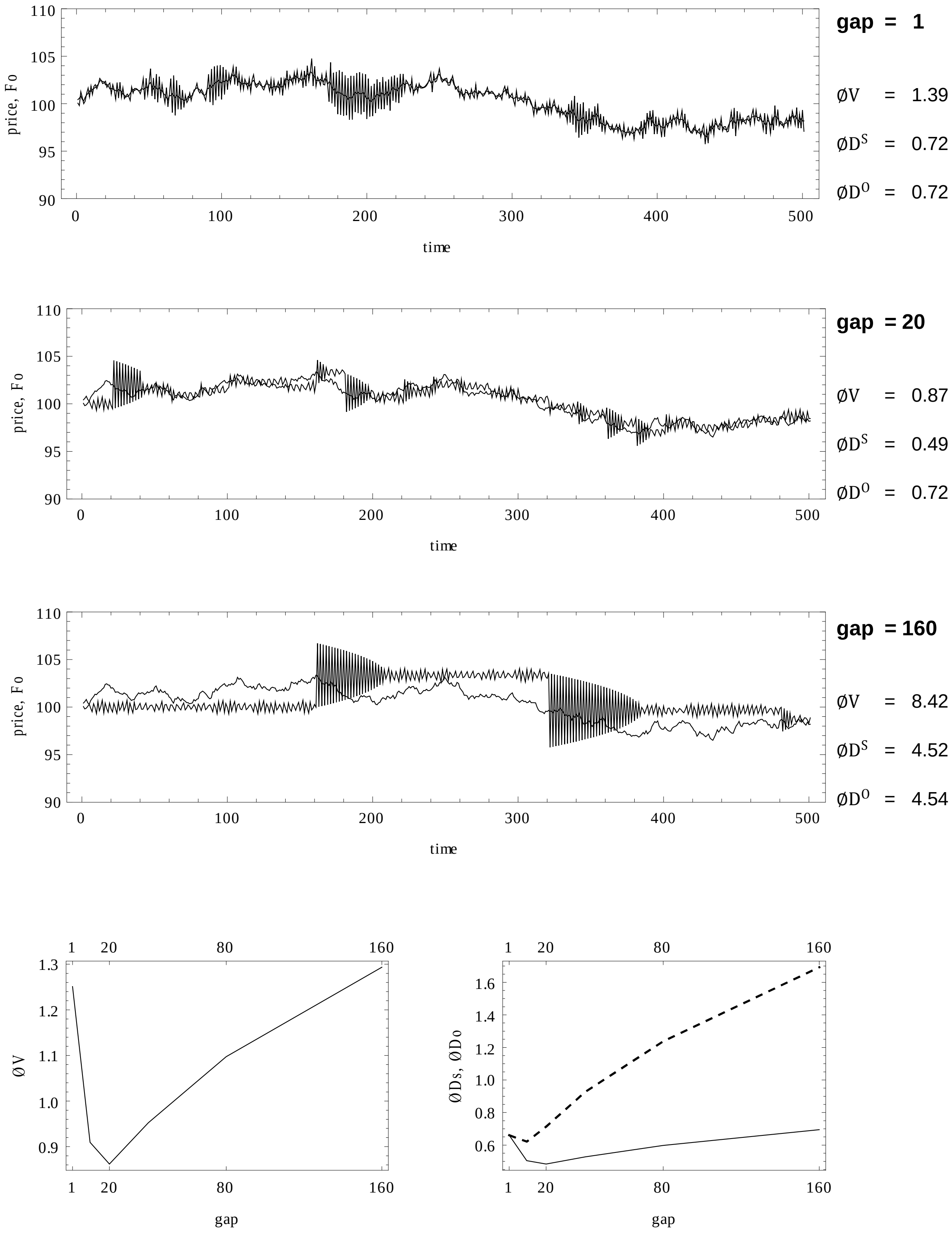

Figure 3: The first three panels show the evolution of objective fundamentals (thin line) and the dynamics of prices for different information-gaps. In the first panel the dynamics of prices covers the evolution of fundamentals visually. The measure of volatility (ØV), subjective distortion (ØD^s), and objective distortion (ØD^o) for the respective simulation run are appended on the right. The random walk of objective fundamentals is the same for all three simulations. The left panel below illustrates volatility, the right panel subjective and objective distortion (dashed line), depending on the gap. Volatility and distortions were measured for gaps of 1, 10, 20, 40, 80 and 160; results are based on twenty simulation runs of 5000 periods each for every gap. Parameter a^C = 2. For other parameters see section "calibration".

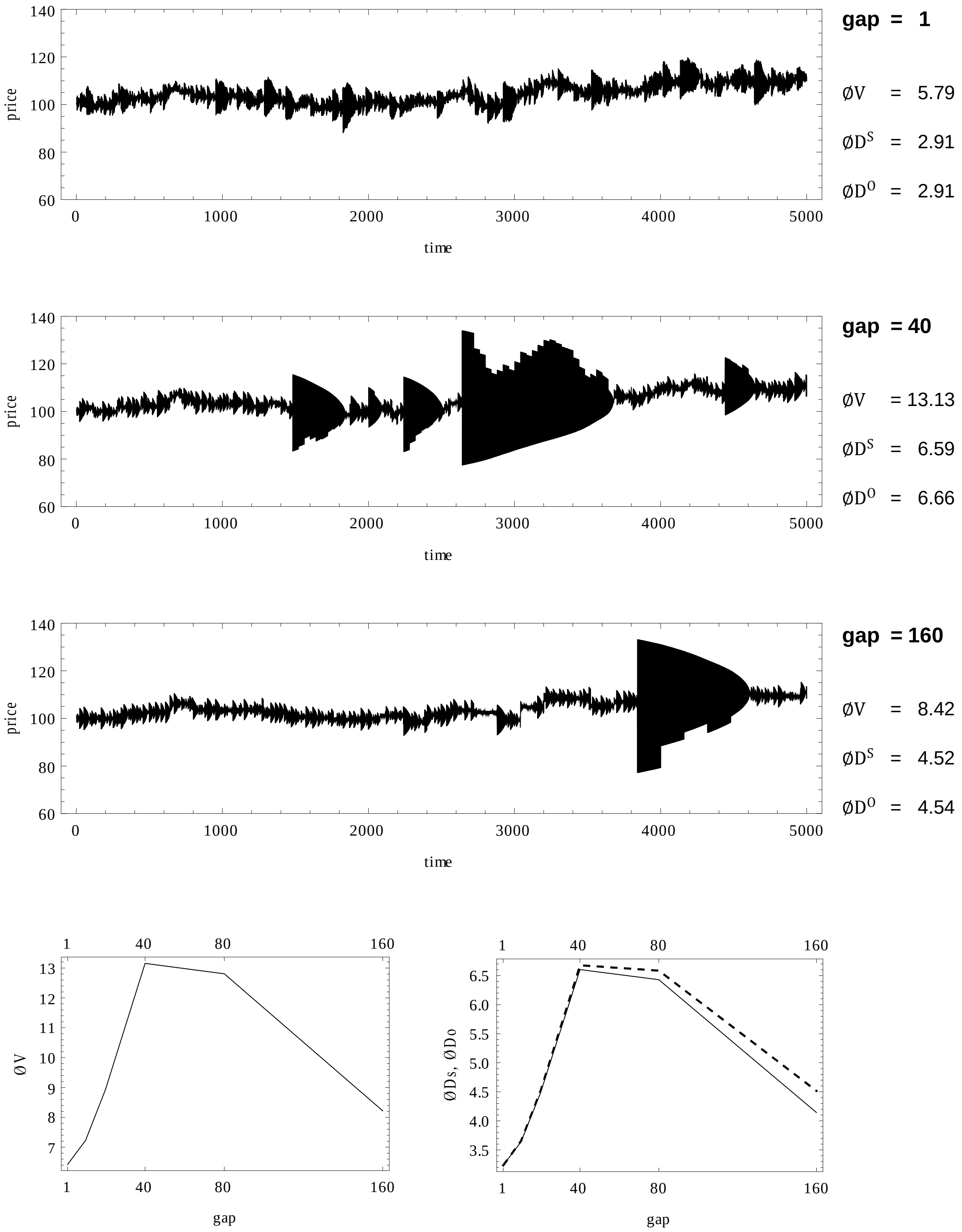

Figure 4: Same as in figure 3, except simulation run panels display prices only. Now parameter α^C = 8. For other parameters see section “calibration”.

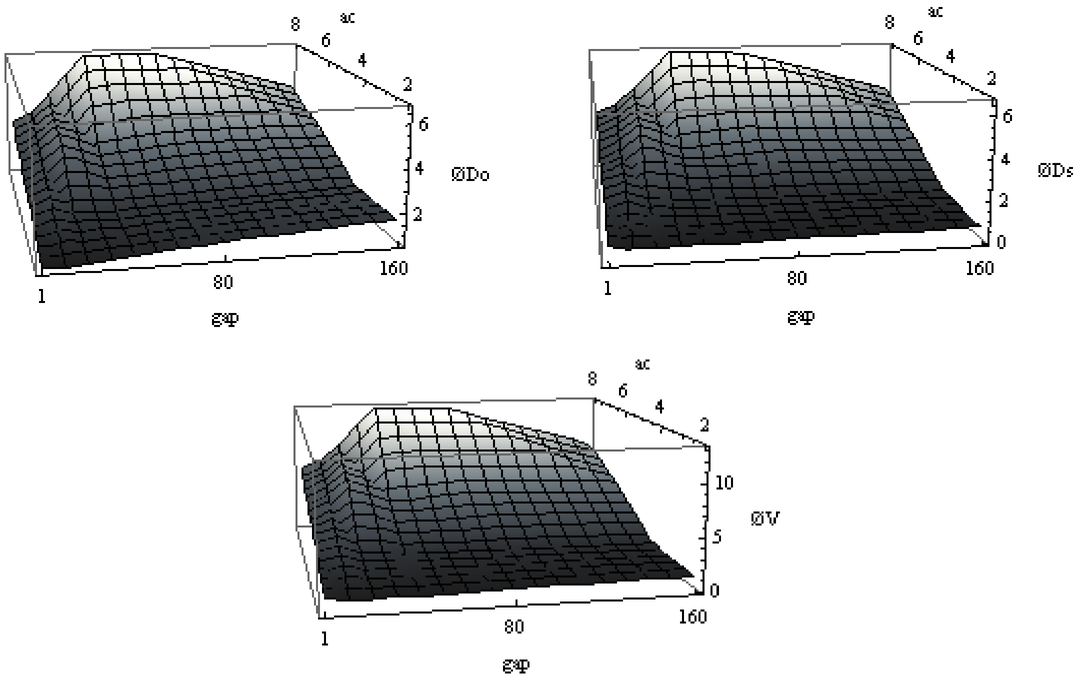

Figure 5: Volatility (left) and subjective distortion (middle) and objective distortion (right) for different combinations of gap and parameter a^C. a^C was set to 2, 4, 6, and 8. Chosen gap lengths were 1, 10, 20, 40, 80 and 160. Average volatility and distortions of every combination are based on twenty simulation runs of 5000 periods.

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