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„Stochastic fundamentals and multiple regimes in an experimental double auction asset market"

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Abstract

Asset market experiments have historically evolved toward more intuitive paths of the fundamental value -from continuously declining to constant to fluctuating. The present study takes the next logical step by implementing stochastic fundamentals, combined with two different regimes that simulate bull and bear markets. Stochastic fundamentals offer the unique opportunity to experimentally investigate whether traders in asset markets are prone to the gambler´s fallacy and the hot-hand fallacy, and to locate the turning point between these biases. Moreover, the experiment serves as a robustness check for earlier studies. Results clearly show that an intuitive setup with stochastic fundamentals alone does not suffice to establish efficiency. It is higher than in designs with continuously declining fundamentals, but lower than where fundamentals are constant. Though not all results are significant, they qualitatively confirm findings from field studies whereby traders can outperform the market by buying stocks on good news and selling on bad news. Only where streaks are very long, hot-hand beliefs may dominate.

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1 Introduction

In asset markets, buyers and sellers meet and may interact. Asset prices indicate whether a purchase or a sale will increase the utility of participants. A transaction typically takes place if both parties deem the trade to be in their favor. This may happen for a number of reasons, including divergent time preference rates or distinct risk types.

An efficient market is defined by prices that appropriately reflect the underlying fundamental (Fama, 1970). Measuring the fundamental value (FV) in real asset markets is fraught with difficulty, but it has been widely argued that fundamentals and prices are rarely the same and may diverge significantly (Zhong, Darrat & Anderson, 2003).

An asset market bubble is characterized by prices persistently deviating from fundamentals (e.g. Haruvy & Noussair, 2006; King, Smith, Williams & van Boening, 1993). Popular historic examples are the Dutch tulip mania in 1637, the stock market bubble of the late 1920s in the United States and the Japanese asset bubble of the 1980s. A more recent example is the US housing bubble which served as a prelude to a severe recession in the United States in the years 2008-2009, and to the international financial crisis.

When bubbles burst, this frequently disturbs an economic equilibrium. In the follow up, GDP growth can decline, causing higher unemployment. The resulting costs can exceed the gains incurred during the boom before the bust. Negative economic shocks arguably reduce confidence and trust within an economy. These lasting consequences may severely delay economic recovery (Bordo, 2003; Bordo & Jeanne, 2002).

A timely and appropriate response to emerging bubbles could reduce costs by dampening economic disturbances, support an efficient capital allocation and thereby improve societal welfare (Roubini, 2006). To this end, research on market inefficiencies aims to identify their causes as well as potential remedies.

Experimental asset markets are a useful vehicle for such research, because they overcome the problem of immeasurable fundamentals. Since Smith, Suchanek & Williams (1988, hereafter SSW) first created an experimental double auction asset market and observed bubbles and crashes, many related studies have followed. The results fuel a debate on whether bubbles also appear in real asset markets and, if so, whether bubbles are frequent or rare.

While SSW and other early experiments (King et al., 1993; Porter & Smith, 1995) use a design with frequent dividend payments and continuously declining fundamentals,[1] later studies hold the fundamental constant by introducing an expected dividend of zero, combined with a final buyout (Noussair, Robin & Ruffieux, 2001). Results are robust to various changes of the experimental setup (e.g. Oechssler, Schmidt & Schnedler, 2007; Noussair, Richter & Tyran, 2008). They indicate that inefficiencies and bubbles still arise where fundamentals are constant but are less likely to occur. Noussair & Powell (2009) proceed to investigate trading behavior in a market where fundamentals initially rise (decline) and later decline (rise), i.e. fluctuate in the course of the experiment. Though an evolution toward more realistic trends of fundamentals -from continuously declining to constant to fluctuating- is thus noticeable, all previous studies have in common that the track of the fundamental is *predetermined*.

The present study goes one step further by using a design with *stochastic* fundamentals. The final buyout depends on how often the asset value rises and falls, which is determined stochastically. The expected final buyout varies in the course of the experiment. The basic change is not the mere implementation of a stochastic process. The dividend payments in almost all former studies are also determined stochastically. The vital modification in the present study is that the stochastic process affects the FV. To simulate a business cycle, I introduce a positive autocorrelation of events. Specifically, I introduce two different *regimes*. In the terminology of stock traders, such prolonged phases of expansion and contraction are widely known as bull and bear markets (Gonzalez, Powell, Shi, & Wilson, 2005; Lunde & Timmermann, 2000).[2] The idea of investors' beliefs in persistent regimes is also modeled by Barberis, Shleifer & Vishny (1998). I am not aware of any previous experimental study where the track of the fundamental is not known ex ante.

The stochastic process is also advantageous because recent evidence suggests that -despite the seemingly simple tracks of the fundamental in former experiments- subjects are often confused, because they "interpret the task they face in an experiment against the background of their past experiences and personal knowledge" (Kirchler, Huber & Stockl, 2012). Predetermined fundamentals contradict these experiences. By contrast, a random

[1] In these studies the fundamental equals the expected dividend times the number of remaining periods.
[2] "In stock market terminology, bull (bear) market corresponds to periods of generally increasing (decreasing) market prices" (Chauvet & Potter, 2000).

walk is what most people have in mind when they think about the stock market. The new design serves as a check whether the results of former experiments are robust to an implementation of stochastic fundamentals.

Moreover, the stochastic fluctuation of the FV offers the unique opportunity to investigate trading behavior with respect to the gambler´s fallacy (GF) and the hot-hand fallacy (HHF) and thereby contribute to another strand of literature. Fallacious beliefs that random sequences exhibit negative autocorrelation (the GF) or positive autocorrelation (the HHF) have implications for asset markets: Loh & Warachka (2012) find that an average trader is prone to the GF and that a trading strategy of buying (selling) stocks on streaks of positive (negative) earnings surprises creates additional returns. While these fallacies and their implications have been studied both in the field (Suetens & Tyran, 2012; Croson & Sundali, 2005) and in non-asset market laboratory experiments (Ayton & Fischer, 2004; Rapoport & Budescu, 1997), to my knowledge the present study is the first to illuminate the effect of the GF and the HHF in an experimental asset market.

The present study is an attempt to implement an intuitive design. The reduction of confusion combined with stochastic fundamentals allows focusing on specific biases such as the GF and the HHF. Results indicate that mispricing is reduced compared to the classical SSW design. However, it is higher than in treatments with constant fundamentals. Trend discovery is better when fundamentals are falling than when they are rising. There is evidence that prices are too low when fundamentals are increasing and too high when fundamentals are decreasing. These effects become stronger with longer streaks and indicate that an average trader is prone to the GF. There is also some indication that the HHF starts to dominate when streaks reach a certain length. Though not all results are significant, they point in the same direction like many field studies. Accordingly, buying on good news and selling on bad news may allow traders to outperform the market.

The study is structured as follows. Part 2 reviews relevant previous work. Part 3 presents the hypotheses. A detailed overview of the experimental setup and its implementation is given in part 4. Part 5 discusses the results. Finally, part 6 comments on limitations of the study, gives an outlook on further research and concludes.

2 State of research

This section reviews relevant prior research. Section 2.1 surveys the literature on rationality in asset markets and irrationality at the level of individuals. The associated concepts of efficiency and systematically biased beliefs are of great importance to the present study. Section 2.2 discusses the suitability of laboratory experiments to investigating the aforementioned aspects. Related evidence from field data and from laboratory experiments is provided in sections 2.3 and 2.4 respectively. The closing section 2.5 explains why this investigation fills a gap, adds evidence to the existing literature and may also offer new insights regarding price discovery in asset markets.

2.1 Theoretical background

2.1.1 The efficient market hypothesis

What is the equilibrium in asset markets? Does it exist and, if so, will it obtain? The *efficient market hypothesis* (EMH) relates to these questions. In his seminal paper, Fama (1970) concludes that there is no clear evidence that prices in asset markets do not “fully reflect all available information”. Neither the existence of transaction costs, nor limited access to all available information, nor disagreement among investors about the right interpretation of information lead to inefficient price discovery.

Instead, Fama assumes that prices do reflect the FV adequately on the basis of expected returns. This does not only imply that prices instantly react to new information, but also that the price level is correct. According to the EMH it is impossible to forecast the performance of a stock by evaluating a company´s balance sheet or the like – once new information is available, it immediately affects the price. The only way to outperform the market is to illegally use insider information. The assumptions and predictions of the EMH are in line with the neoclassical view of utility maximization by the *homo economicus*.[3] It has been widely discussed whether asset markets are efficient in this sense or whether prices and fundamentals occasionally diverge.

A considerable obstacle to testing the EMH is the fact that the FV of an asset is unobservable in the field. Measurement of the fundamental is approximate and possibly biased. For a

[3] The term “homo economicus” refers to the assumption that human actors are rational utility-maximizers.

stock it equals the expected discounted stream of dividends (Ball & Holt, 1998). Via this definition the FV is based on expectations. As long as the expectations are sufficiently high or low, every price can be justified. The EMH has provoked much critique, because a theory which claims to explain everything[4] but cannot be tested for accuracy is unsatisfactory.

Testing the EMH requires a model which provides the researchers with the FV of an asset. Afterwards, this value can be compared with the transaction prices. In fact, these tests of the EMH are joint tests about the EMH and the hypothesis that the specific model for the expected returns is correct. A rejection of the joint hypothesis cannot clarify where the error is located: Whether the market is inefficient or the model is wrong (Fama, 1991).

Additional insights concerning decisions under risk were provided by Kahneman & Tversky (1979) in their *prospect theory.* They claim that biases such as loss aversion are common. The existence of biased beliefs may provide a basis for challenging the EMH. For asset markets, loss aversion would imply a price discount for risky assets like stocks and a price premium for assets which are regarded to be safer, e.g. some government bonds. This adds new aspects to the picture of the homo economicus. The authors point out that even a rational and utility maximizing behavior does not exclude biases like personal risk preferences.

In their survey, Beechey, Gruen & Vickery (2000) conclude that the EMH often approximates actual pricing adequately. Asset prices seem to follow a random walk in the short run and react rapidly to new information, and fund managers are not able to beat the market. These facts support the EMH. However, evidence also shows that even strong misalignments which may persist for extended periods of time cannot be ruled out per se. Some spectacular increases and subsequent crashes of asset prices indicate that price discovery is not always efficient. The authors state that some crashes, including the 22% decline of the S&P 500 on October 19th 1987, occurred without new information that would justify such a remarkable price adjustment.

Nevertheless, the EMH is a good starting point for investigating price discovery. It provides a clear and precise forecast of how prices and fundamentals are related: They are identical. Regardless of whether the EMH is valid, this prediction serves as a useful benchmark. Any

[4] "Everything" here means that, however unjustified and strange the price of an asset may seem, according to the EMH it reflects the FV.

deviation can be related to it and can be classified. The popularity of the EMH has considerably changed over the decades, leading Shleifer & Summers (1990) to remark that, “if the efficient markets hypothesis were a publicly traded security, its price would be enormously volatile”.

2.1.2 The gambler´s fallacy and the hot-hand fallacy

The *law of large numbers* says that the results obtained from a random process should converge to the expected values when observing sufficiently many signals of the process. According to Tversky & Kahneman (1971), many people wrongly apply this insight to processes with only few available signals, i.e. they overestimate the probability that the distribution of small samples correctly represents the population. They believe in the *law of small numbers,* often referred to as *local representativeness*.

The expectation that small samples are likely to resemble large samples is wrong. Due to the variance -which is often underestimated- the number of observations needed to adequately represent the population is regularly much higher than most people would expect. For scientific work this implies that large samples are essential. Otherwise, deviations from the normal distribution or another reference distribution will not be identified due to statistical insignificance.

Furthermore, people tend to expect a random process to be self-correcting. They find it hard to believe that many processes are completely independent from earlier outcomes – that there is no autocorrelation within a process. Instead, especially a belief in negative autocorrelation is often prevalent for signals that are identically independently distributed (i.i.d.).

Rabin (2002) models this biased belief. He assumes that people who face i.i.d. signals often think that the signals are draws without replacement from an “urn” with a finite number of balls ($N<\infty$). This directly leads to the *gambler´s fallacy* (GF). The smaller the number of balls N in the urn, the stronger is the expected negative autocorrelation. As the number of balls becomes larger and diverges to infinity, the agent becomes perfectly Bayesian.

People who believe in the law of small numbers or wrongly expect a negative autocorrelation for non-autocorrelated random sequences are prone to the GF. It is a popular fallacy. Rapoport & Budescu (1997) investigate how people predict the outcome of flipping a perfectly fair coin. After it has been flipped three times, subjects expect the next outcome to "balance" the earlier ones. This finding is in line with the belief in the law of small numbers. But subjects put even more weight on the more recent draws. This indicates a belief in negative autocorrelation. For example, when the last three flips of the coin were tails each, on average subjects think that the next flip will be heads with a probability of 70%. Similar results were obtained from roulette players in a casino. The longer a streak of one color has persisted, the more players bet on the other color for the next round (Croson & Sundali, 2005).

Different from the bias of believing in the law of small numbers, the belief in negative autocorrelation does not even hold for large sample sizes. If a coin is truly perfect, the probability for the next flip to be heads or tails will always be 50%. The probability of drawing a specific color in roulette of course does not change either.

By contrast, the *hot-hand fallacy* (HHF) is the erroneous belief that a streak of same outcomes of a random process increases the probability that the streak will continue. The labeling of the fallacy comes from basketball, where fans sometimes believe that players who have scored several baskets is a row have a "hot hand" and are more likely than normally to score the next basket, too. Here a belief in positive autocorrelation is prevalent. At first glance, the GF and the HHF seem to contradict each other: While the GF involves the belief that streaks will reverse, the HHF involves the belief that streaks will persist. However, there is some evidence that the two fallacies are related.

Rabin & Vayanos (2009) argue that the GF is a primitive bias and the HHF may arise from it. Primitive means that a belief in excessive reversals persists even when the subjects are told that signals are not autocorrelated (e.g. the toss of a fair coin). The HHF does not usually arise under parameter certainty, but tends to arise when "people are uncertain about the mechanism generating the data". The recurrence of the same signal several times in a row may mislead people into wrongly assessing the probabilities of the underlying process. People imagine that they spot patterns in random sequences. Because they find it hard to believe that the toss of a fair coin yields to heads (or tails) several times in a row, they start to think that the coin is not fair. They expect the streak to continue. Hence, their belief can switch from the GF to the HHF.

Daniel, Hirshleifer & Subrahmanyam (1998) focus on the asset market. They invent a model where irrationality of investors is caused by overconfidence and biased self-attribution. Overconfident traders put too much weight on private signals relative to public signals. Private signals lead such traders to overreact -i.e. they buy on good news and sell on bad news- while public signals are neglected. Traders with biased self-attribution credit their own forecasting skills whenever new information confirms an earlier trade, while new information with a disconfirming character is regarded either as a noisy signal or even as sabotage. This model of investor irrationality can explain a positive autocorrelation of asset pricing in the short run. In the longer run there might be reversals, i.e. a negative autocorrelation.

Another model that explains both gambler´s- and hot-hand fallacy behavior is offered by Barberis et al. (1998). A company´s earnings in each period are either 1$ higher or lower than in the previous period. The direction of the fluctuation is determined by a random walk. Agents believe that the earnings switch between two different regimes. In one regime, earnings changes tend to reverse from period to period. The other regime tends to repeat earlier earnings changes. Agents use earlier outcomes to predict future ones. This model is able to explain both underreaction and overreaction.

Jørgensen, Suetens & Tyran (2011) find that an average Danish lotto player is prone to both the GF and the HHF. After a specific number has been drawn, less players move towards this number for the next draw. People avoid the number, because they consider it less likely to be drawn again. Other numbers appear to be the better bet. However, when the same number is drawn several times in a row, the number eventually becomes more popular. After it has been drawn in four consecutive drawings, more people move towards this number than to a number which has not been drawn the previous time. They begin to believe in positive autocorrelation. Furthermore, the authors find that players who are prone to the GF are also more likely than other players to be prone to the HHF.

2.2 Properties of experimental economics

Many processes in the real world are complex. The great number of determining factors makes it hard for the researcher to identify crucial parameters. Feedback effects cannot always be ruled out, and they reduce statistical significance. As a result, field researchers often depend on large data sets to obtain significant results. Costs in terms of time and money are usually high.

A major advantage of experimental economics is the reduction of complexity. This allows both subjects and experimenters to concentrate on few relevant factors. Ideally, subjects fully understand the task. Typically, subjects are incentivized by money. Their decisions decisively affect their final payment. This feature is an advantage over surveys where answers are not incentivized.

In real asset markets, the unobservable fundamental is a major obstacle to investigating efficiency. Experimental asset markets have the essential advantage that they overcome this problem. Normally, subjects are provided with accurate information about the FV. If existent, a divergence of prices and fundamentals can easily be observed and measured. Such a divergence would contradict the EMH at least at an experimental level.

Once an interesting feature of trading behavior, such as systematic mispricing, is identified, experiments allow for its systematic investigation, because parameters can easily be varied in a controlled way. This facilitates the distinction between critical and irrelevant parameters, makes it easier to establish causality and therefore increases the *internal validity* of results (Roe & Just, 2009). Field studies have far more parameters, many of which are not adjustable. This makes it difficult to ascertain which parameter affects a trader´s decision and to isolate its effect.

However, like all research methods, experimental economics also suffer from some drawbacks. First of all, there is a selection bias. The pool of people from which subjects are drawn is often small and unlikely to be representative of the population. Usually, the fraction of students is high. Furthermore, the investigated markets are small in terms of scale, number of traders and monetary stakes (Noussair & Powell, 2009), and the artificial atmosphere in the laboratory may influence subjects.

External validity is the ability "of generalizing results from laboratory to non-laboratory conditions" (Guala & Mittone, 2005). In their comparison of various research methods, Roe & Just (2009) argue that laboratory experiments have relatively low external validity compared to field experiments or field studies, but that they are useful for generating observations and hypotheses worthy of further investigation. According to the authors, experimental results may serve as a good starting point to eventually increase external validity.

2.3 Evidence from field data

The GF and the HHF have some specific implications concerning pricing at asset markets. As described below, a non-biased trader may benefit from inefficient price discovery by executing specific trading strategies.

If the average market participant is prone either to the GF or the HHF, price discovery will be inefficient. Imagine a listed company which had several positive earnings surprises in a row. A trader prone to the GF (hereafter GF-trader) wrongly anticipates the next earning surprise to be negative. Therefore he sells the company´s stocks or at least buys fewer additional stocks than would an unbiased trader. This causes a relative drop in the stock price. But another trader may be prone to the HHF (hereafter HHF-trader). He is willing to buy more additional stocks than a rational trader in expectation of further positive surprises. The price goes up relative to the FV. Because GF-traders act oppositely to HHF-traders, valuation effects cancel each other out. Therefore the price will only deviate from fundamentals if traders are prone to one of the fallacies *on average*.

GF-traders dampen price volatility: Selling stocks after positive surprises causes a drop in the price relative to the fundamental. Likewise, buying stocks after negative surprises causes a relative rise in the price. GF-traders can cause *momentum* in asset markets: In the longer run prices will reflect fundamentals again and after a first underreaction of the investors a catching up process leads to positive autocorrelation between prices and earnings surprises.

In contrast, traders prone to the HHF fallacy boost volatility: They buy after good news and therefore increase the price when the fundamental is high already. The same holds for the other direction: When the fundamental is low after a negative earnings surprise, they excessively sell stocks and cause a further drop in the price below the fundamental. HHF-traders can cause *reversals* in the longer run. The overshoot in the price immediately after the earnings surprise causes an adjustment process afterwards.

Once traders in a market are identified as prone to one of the fallacies on average, there might exist specific trading strategies to create additional returns. If price discovery is systematically inefficient, it is possible to beat the market by targeting the inefficiencies. A wrong valuation offers opportunities as long as it is only temporary. Then sooner or later mispricing will vanish and the price will return to correctly reflecting the underlying fundamental. From a whole body of existing research a few results are depicted here.

Loh & Warachka (2012) create a momentum portfolio. They investigate a strategy of buying stocks on streaks of positive earnings surprises and selling them on streaks of negative ones. By executing this simple strategy, average returns increase significantly. Their results indicate that an average trader is prone to the GF. By implementing a *momentum strategy* - which imitates trading behavior of a HHF-trader- the returns rise. Similar results are obtained by Jegadeesh & Titman (1993). Evidence that markets take time to process new data is provided by Chan, Jegadeesh & Lakonishok (1996). This time lag can be used to outperform the market in the long run. The authors state that investors are more likely to trust new information that confirms earlier news. In contrast, new information that disconfirms earlier news is discounted by an average trader. The awareness that agents tend to be slow to change their beliefs in face of new evidence is also called *conservatism* (Barberis et al., 1998).

Additional aspects concerning momentum strategies are provided by Cooper, Gutierrez & Hameed (2004). By focusing on past stock performance -instead of earning surprises- the authors find that the current state of the market is of crucial importance. Only markets which had positive returns over the last three years are suitable for momentum strategies. Otherwise the additional returns are statistically insignificant.

Though many studies come to the conclusion that momentum strategies are a proper instrument to generate extra returns, some doubts should not be neglected. Critics do not doubt that due to persistent irrationality markets can be inefficient. However, they question the possibility that this inefficiency can be strategically exploited, because the timing of irrationality and its effect on pricing are impossible to predict with any degree of accuracy.

Smart investors should apply the relatively simple trading strategies described above in order to benefit from it. However, this would lead to a decline of the momentum gains and efficiency would be reestablished eventually. It seems unlikely that no or only few investors try to benefit from momentum strategies so that momentum gains persist. Strong evidence that supports the EMH comes from the performance of actively managed funds. Though much real time information is available to professional fund managers, most of them are not able to beat the market. There is some evidence that most of the actively managed funds and all actively managed funds on average underperform their benchmark indices (Malkiel, 2003).

Apart from that, most studies that apply momentum strategies ignore transaction costs. Taking these unavoidable costs into account reduces additional returns obtained from any trading strategy. Moreover, some studies come to the opposite conclusion, namely that past winners perform worse than past losers in the long run (DeBondt & Thaler, 1985). This would indicate a short term overreaction, i.e. a behavior which can be explained by the HHF.

2.4 Evidence from laboratory data

King et al. (1993) define bubbles as "trade in high volumes at prices that are considerably at variance from intrinsic values". The results of SSW (1988) challenged the EMH and pushed research in experimental asset markets. The systematic mispricing which is prevalent in the setup of SSW is surprising. According to the EMH prices should accurately reflect fundamentals. The finding that asset prices are far above fundamentals and crash in the end is robust to various changes of the setup, including short selling, brokerage fees and different dividend payments (Caginalp, Porter & Smith, 2000). Though Grinblatt, Kehoharju & Linnainemma (2011) find that investors in real asset markets have higher IQs than an average individual and conclude that this may enable them to trade at more efficient prices than usually observed in experimental studies, wrong valuation in experimental asset markets raises the question whether valuation in real asset markets is also wrong.

The setup of SSW implies frequent dividend payments of varying magnitude. The FV equals the expected sum of dividends. The fewer periods remain, the lower is the FV. This implies that the value of the asset declines from period to period. Conversely, the amount of money circulating in the market increases due to the dividend payments. The cash/asset ratio (C/A ratio) multiplies severalfold in the course of the experiment.

Kirchler et al. (2012) take this as their point of departure. They check how the trends of the FV and the C/A ratio influence results. The authors create four different treatments. The path of the FV is either declining or constant. The C/A ratio is either increasing or constant. In each treatment one specific combination of these characteristics is realized (see table 1).

The authors find that the path of the fundamental has a significant impact on price discovery. When the fundamental declines continuously, mispricing and confusion are prevalent. Bubbles only occur when a declining fundamental is combined with an increasing C/A ratio (like in the setup of SSW). This finding is in line with Smith, van Boening & Wellford (2000). In contrast to that, a constant fundamental value leads to much less mispricing and to a highly efficient market. When the fundamental value is constant it is negligible whether or not the C/A ratio is also constant.

FV cash/asset ratio	Decreasing	Constant
Increasing	- Overvaluation - Mispricing - Confusion	- High efficiency
Constant	- Mispricing - Confusion	- High efficiency

Table 1: Results from the study of Kirchler et al. (2012). Source: Own compilation

Another interesting finding in the paper by Kirchler et al. (2012) concerns the impact of the wording in the instructions for the experiment. The authors repeat the classical SSW treatment with declining fundamentals and an increasing C/A ratio. But instead of “stocks” they now label the asset as “stocks of a depletable gold mine”. This seemingly small change leads to significantly less mispricing and prevents bubble formation. The authors explain this finding by reduced confusion among the subjects. These findings call the external validity of many other results into question. When subjects´ confusion is the main driver behind bubble formation in experimental markets, then real markets are likely to be far more efficient. Another indication that points in this direction is provided by Lei & Vesely (2009). They find that bubbles can be eliminated when the dividend process is explained very carefully. A more intuitive environment might increase efficiency and external validity.

Cheung, Hedegaard & Palan (2012) argue that common expectations among traders are important to achieving efficient pricing in asset markets. They find that price discovery with trained subjects is as bad as with untrained ones as long as subjects are not aware that all traders have been trained. Only training *and* the knowledge that all subjects are experienced are sufficient to increase efficiency. They conclude that confusion is not the main cause of the occurrence of bubbles. Strategic considerations of subjects may play a more important role. The idea that common expectations are responsible for efficient pricing is supported by Smith et al. (2000). The authors analyze how the timing of dividend payments influences pricing. They find that a periodic payment leads to price bubbles, whereas a single final payment may prevent bubbles. The authors state that a concentration of the dividend payment at a single point fosters common expectations among the subjects. Like Cheung et al. (2012) they conclude that this encourages more rational behavior.

The impact of speculation on the price is investigated by Lei, Noussair & Plott (2001). They define speculation as *conscious mispricing in order to realize capital gains*. Consider a rational trader who assumes the price to increase irrespective of how the fundamental will change in the forthcoming periods. For him it is rational to buy an asset for a price above the FV, because he will subsequently be able to resell it for an even higher price. Note that it is not required that irrational traders are in the market. It suffices that a rational trader assumes other traders to behave like irrational ones. This could explain why mispricing occurs even where all traders are rational.

To measure the influence of this speculation type, Lei et al. (2001) create an asset market in which speculation is not possible. Subjects are assigned to be either buyers or sellers. Neither reselling nor rebuying is possible in this setup. If mispricing is due to speculation, price discovery will be efficient in this setup. Strategic considerations of traders are eliminated. The authors find that speculation is not necessary for bubbles to occur. The amount of mispricing is similar to a setup where speculation is possible.

Increasing a trader´s experience by repeating the market with the same subjects several times is another way of enhancing efficiency (Dufwenberg, Linqvist & Moore, 2005). However, this method has the disadvantage that repeat experiments are costly in terms of money and time. Furthermore, a change of the dividend parameters or an increase in liquidity may lead to a recurrence of inefficiency (Hussam, Porter & Smith, 2008).

The impact of a nominal shock is analyzed by Noussair et al. (2008). Throughout their experiment, the fundamental is constant in real terms. They observe that overvaluation only takes place when the shock is deflationary. By contrast, an inflationary shock does not significantly affect efficiency compared to a no-shock treatment. The authors point to nominal loss aversion as a possible explanation. This may also account for overvaluation in designs with constantly declining fundamentals.

Noussair & Powell (2009) investigate how the time path of the FV influences trading behavior. By introducing dividends and taxes the authors create two different treatments. One treatment, which they call the "peak" treatment, has an increasing FV in the early periods and a declining one in the later periods. The other treatment, which they call the "valley" treatment, has a declining FV in the early periods and an increasing one in the later periods. Both treatments are repeated four times with the same subjects to increase their experience.

The authors find that the time path has an impact on price discovery. In the early markets bubbles occur in both treatments. But whereas experienced subjects trade at prices close to the FV in the peak treatment, experience does not help in the valley treatment. Even after three repetitions, subjects fail to trade at efficient prices. Only in the peak treatment do prices and fundamentals simultaneously change direction. In the valley treatment, prices systematically change direction later. The authors conclude that the time profile of the fundamental affects price discovery.

An experiment that is concerned with beliefs in the GF and in the HHF is conducted by Asparouhova, Lemmon & Hertzel (2009). Subjects face a sequence of eight binary outcomes and have to specify their belief about the ninth outcome. Unlike in the study of Bloomfield & Hales (2002), subjects are not told that the signal generating process is a random walk. The authors find that subjects are GF-biased and expect signals to be mean-reverting when streaks are short. However, where streaks persist, subjects become prone to the HHF: the longer the streak, the higher the assigned probability that streaks will continue. The authors conclude that their data fits better with Rabin´s model (2002) than with the model of Barberis et al. (1998).

2.5 Conclusion

The efficient market hypothesis predicts that prices and fundamentals coincide in asset markets. This implicitly denies the existence of an average biased trader. However, field and experimental studies not directly concerned with asset markets (Lotto, flip of a coin, etc.)

provide strong evidence that people are systematically biased and prone to irrational behavior because they are victims of popular fallacies. Field studies of asset markets offer ambiguous evidence regarding the EMH. There is very little research on the GF and the HHF in experimental asset markets. This gap should be filled to add new aspects to the ongoing debate.

Evidence from experimental asset markets challenges the EMH. A typical observation -especially with inexperienced subjects- is that bubbles arise after a few trading periods. Then prices stay at high levels for a considerable number of periods and decline rapidly towards the end of the experiment. However, results do not indicate that either the GF or the HHF are responsible for this severe mispricing. Confusion may be an explanation. Kirchler et al. (2012) provide evidence that a more intuitive setup may increase efficiency.

Fama (1997) criticizes that some authors are aware of confusing patterns in their experimental design but do not try to avoid them. He argues that a sensational result is often welcome because it attracts greater attention. I do not go that far. However, it seems worthwhile to create a design where confusion is reduced, in order to focus on specific biases such as the GF and the HHF.

There are various different ways of increasing efficiency, namely

(1) increasing a subject´s experience by repeating the same setup several times,[5]
(2) holding the fundamental constant in nominal and real terms,[6]
(3) implementing an intuitive setup.

It is not entirely clear what exact properties of a design are responsible for improved price discovery. It could be a reduction of confusion, as suggested by Kirchler et al. (2012), or the creation of common expectations, as claimed by Cheung et al. (2012), or a combination of both.

Possibilities (1) and (2) have been implemented and analyzed in many studies. However, they suffer from a lack of external validity. In real asset markets, it is extremely unlikely that market participants repeatedly face exactly the same situation -including general economic condition, interest rates, mood on the financial market, condition of a company´s specific sector, etc.- thereby gain experience and are thus able to trade at rational levels. Nor is the

[5] The finding of Noussair & Powell (2009) is an exception in this respect.
[6] At least an inflationary shock has to be avoided (Noussair et al., 2008), see section 2.4.

fundamental of a stock usually constant over extended periods of time. That is why I concentrate on possibility (3) and use an intuitive setup. This may fill a gap in the existing literature.

3 Hypotheses

In the following section the hypotheses are formulated. I justify the assumption that traders are rational in some cases and biased in others, explain why the chosen hypotheses are interesting, and discuss the basic calculations necessary to investigate the hypotheses.

The shares exist for T periods. Trading takes place in N separate markets. Let $p_n(t)$ denote the median transaction price of market n (n = 1, …, N) in period t (t = 1, …, T). Let $FV_n(t)$ denote the fundamental value of market n in period t.

This paper uses two different ways of analyzing price discovery. Mispricing is a measure of the absolute discrepancy between median prices and fundamentals. It is calculated for each market. A lower bound of mispricing is zero. Systematic deviations from fundamentals in one direction across several markets are called overvaluation (OV) when the price is above fundamentals. OV with a negative sign is simply called undervaluation (UV). It is not calculated for each market but across markets that face the same track of fundamentals. An upper bound for OV is the amount of mispricing. To clarify the difference between the two measurements: When the price is too high in one market and too low in another market, then mispricing prevails in both markets. Only the absolute difference matters. An overall OV or UV is not inevitable, because the price disparities in the different markets may cancel each other out. OV and UV measure systematic mispricing in one direction across several markets. Mispricing and OV differ from each other only in periods where the price is above fundamentals in at least one market and below fundamentals in at least one another market. Compared to mispricing, OV and UV are superior indicators of patterns potentially associated with the GF or the HHF. Both measurements are defined as follows:

$$Mispricing(n,t) = M(n,t) = |p_n(t) - FV_n(t)|\,\frac{100}{FV_n(t)}$$

$$Overvaluation(t) = OV(t) = \sum_{n=1}^{N}[p_n(t) - FV_n(t)]\,\frac{100}{FV_n(t) * N}$$

As shown in section 2.4, mispricing is quite common in experimental asset markets, with prices being mostly too high. This finding holds especially for treatments with non-constant fundamentals and is robust to various changes of the design. Since the present study also uses a laboratory experimental approach, it is reasonable to assume that the new design does not eliminate mispricing. However, several properties known to foster mispricing, such as constantly declining fundamentals, constantly increasing C/A ratios and a counter intuitive wording, were avoided in the design of the present experiment. According to Kirchler et al. (2012), this might reduce mispricing and increase efficiency.

Hypothesis 1: Mispricing takes place in the market. However, it is reduced compared to the classical SSW design.

In their study, Noussair & Powell (2009) find that the timing of the change in price trends and trends in fundamentals coincides more closely in the peak treatment than in the valley treatment. In the latter price trends systematically change later than trends of the FV.

I investigate whether this phenomenon survives a change of the experimental design. A peak is defined as a period t_0 where $FV(t_0 - 1) < FV(t_0) > FV(t_0 + 1)$ holds. Likewise, the definition of a valley is a period t_0 where the fundamental is smaller than the fundamentals nearby, i.e. $FV(t_0 - 1) > FV(t_0) < FV(t_0 + 1)$. Based on these definitions, the first and the last period of each session cannot possibly form peaks or valleys. Whereas the first period lacks a preceding period, the last period lacks a subsequent one. Though the track of fundamentals is random in my study, fundamentals are almost certain to change direction in some periods.

Despite Noussair & Powell's finding I assume no time lag between a reversal in the trend of the fundamental and the corresponding change in the price trend either in peaks or in valleys. There is too little theoretical interpretation or experimental evidence available to justify assuming the opposite.

Hypothesis 2: There is no time lag between a change in trend of the fundamental and the associated change in price. This holds for both peaks and valleys.

The third hypothesis refers to the GF and the HHF. If traders are prone to the GF on average there will be systematic OV when the FV has dropped in the previous period and systematic UV when it has risen in the previous period. An average trader´s belief in the HHF would result in the opposite observations, i.e. in OV after the FV has risen and in UV after it has dropped. The linkage between both fallacies -with the idea that the HHF arises from the GF- as proposed in Rabin & Vayanos (2009) and confirmed by Jørgensen et al. (2011) could lead to underreaction to a change in the fundamental when streaks are short enough and to overreaction when streaks have reached a certain length. Baring in mind that there is no clear evidence concerning the GF and the HHF at asset markets, I assume that traders are not biased.

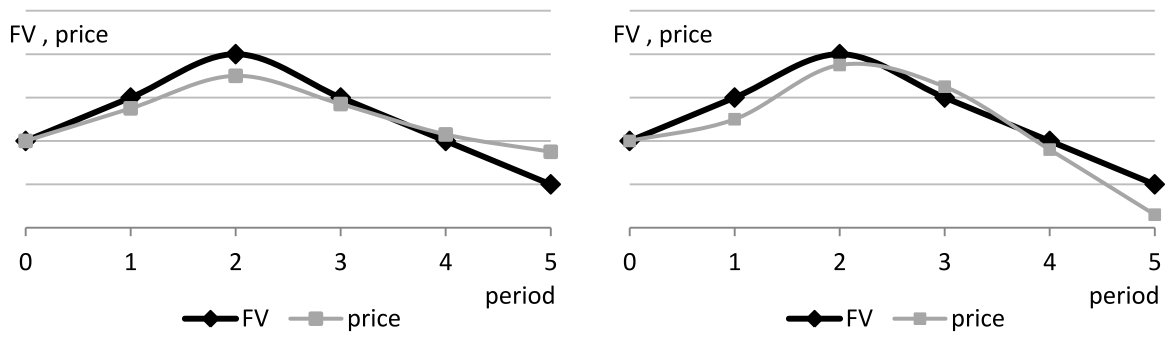

Figure 1: Qualitative OV and UV for pure GF-traders (left) and GF-traders who eventually become HHF-traders (right) as modeled by Rabin & Vayanos (2009).

Figure 1 shows the evolution of OV caused by pure GF-traders (left) and by GF-traders who eventually become HHF-traders (right). Pure GF-traders systematically underestimate a change of the fundamental, i.e. the slope of the price is smaller than the slope of the FV. The alternative model, that the HHF arises from the GF, is pictured in the right diagram. The slope of the price is flatter only in the period after the FV has changed its direction. As streaks become longer, the price overreacts, causing underpricing when fundamentals fall in periods 4 and 5.[7]

Hypothesis 3: There is no systematic OV or UV after certain lengths of consecutive periods with rising or declining fundamentals. Traders are neither prone to the GF nor to the HHF.

The three hypotheses are the main component of the investigation. A goal is to create new evidence which may confirm or refute findings of related studies. Nevertheless, other interesting aspects which are not directly covered by the hypotheses will also be examined.

[7] This is proposed and pictured by Rabin & Vayanos (2009, fig. 2, p. 750) in case of serially correlated signals.

4 The Experiment

This section provides an overview of the experiment. The treatment design is described in section 4.1. Section 4.2 comments on the implementation procedure. Some necessary calculations of the FV are covered in section 4.3. The closing section 4.4 discusses parameters and highlights advantages and drawbacks of the realized design in comparison to previous approaches.

4.1 Treatment design

Trading takes place in a computerized and continuous double-auction market.[8] In 30 consecutive periods assets, called "shares", are traded. Each period lasts 90 seconds. The currency for all trades within the experiment is Taler. Shorting stocks or borrowing money is not allowed. There are no transaction costs. Each market consists of nine subjects. Trading screens continuously provide subjects with real time information about their current amount of Talers, the number of shares in their possession, the FV of a stock and about transaction prices of the current period.

All subjects are identically endowed with 250 Talers and 10 shares. This leads to a total of 2250 (9*250 = 2250) Talers and 90 (9*10 = 90) shares in each market. The amount of Talers and the number of stocks owned by a subject are carried over from one period to the next. After the last period, there is a final buyout for all stocks. How the terminal value materializes is described below.

The track of the FV is affected by two different regimes: the *good regime* and the *bad regime*. In each period, one of the regimes reigns. It is the same for all subjects. Once either the good or the bad regime reigns, there is a 75% probability that it will also reign in the subsequent period. However, in the event of a regime type change, the new type will persist with a probability of 75%. Figure 2 illustrates the stochastic process for the first three periods.

[8] "During each period, any buyer could at any time submit an offer to buy a unit by entering a price at which he was willing to purchase the unit. Similarly, to sell, any individual could submit an offer by specifying a price at which he was offering to sell a unit. At any time, any individual could accept an offer to buy or sell that another participant had submitted, provided that he had sufficient units or funds to complete the transaction. Upon acceptance of an offer, a trade occurred and the cash and the unit were immediately transferred between the two parties" (Noussair et al., 2008).

At this point a term specific to this experiment needs to be introduced: the *current value* (CV). It provides a basis on which the FV is calculated. The first CV is determined by the experimenter and amounts to 20. For simplicity, this starting value is equal for both types of regime. The good regime implies a 10% rise in the CV of the shares. Likewise, the bad regime implies a drop in the CV by 10%. The positive autocorrelation of the track of the fundamental can be interpreted as a business cycle: Once the economy is strong, it is likely to stay strong for some time. However, once there is a crisis, it takes some time to emerge from it. In the final period, the CV equals the FV. In earlier periods, they differ from each other.

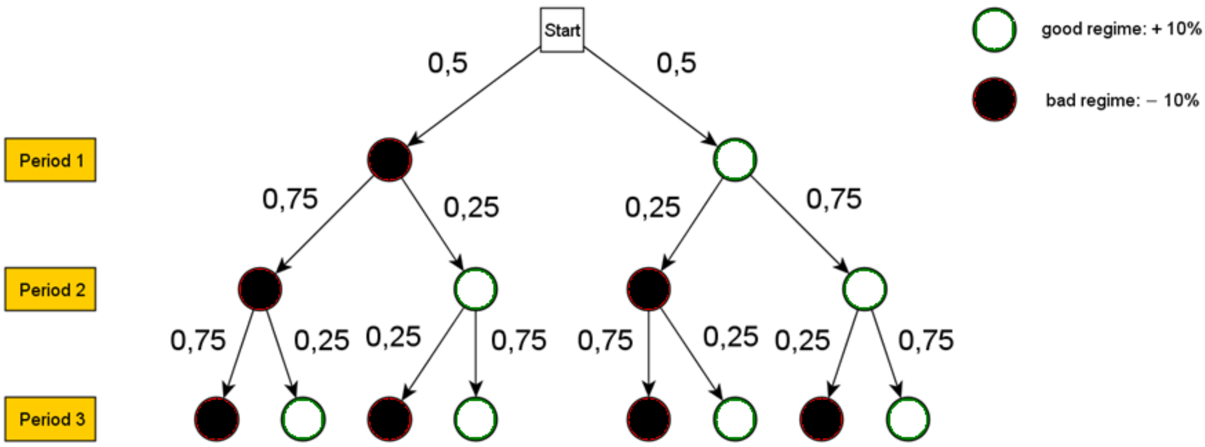

Figure 2: Stochastic process

After the last period has ended, subjects sell the shares in their possession to the experimenter. The price equals the value of shares in the last period. This value is not known ex ante, because it emerges over the course of the experiment from the stochastic process described above. However, as shown in section 4.3, it is possible to calculate the expected value that a share will have in the last period. This expected value is the FV.

Table 2 provides an overview of basic parameters.

Periods	30
Duration of each period	90sec
Markets	4
Subjects per market	9
Initial money [Taler]	250
Initial shares	10
First CV	20

Table 2: Basic parameters of the setup

4.2 Experiment implementation

Four markets were run. Two of them respectively took place simultaneously. The track of the fundamental was the same for these markets. From now on, markets 1 & 2 are called *session A*. Likewise, markets 3 & 4 are called *session B*. A total of 36 subjects participated. The experiment was conducted on July 19th 2013 at the Vienna Center for Experimental Economics (VCEE) at the University of Vienna. The asset market was programmed with z-Tree 3.3.6 (Fischbacher, 2007).

At the beginning of each session, a first part of the instructions was distributed to the subjects. It described the general structure of the experiment and provided detailed information on how to trade in the market. By clicking a button on the screen, subjects acknowledged that they had read and understood the instructions. After the last subject had confirmed, the training periods started. In five training periods lasting 90 seconds each, subjects practiced accepting offers from other traders and making offers to buy or to sell shares themselves. The training periods served the purpose of allowing the subjects to familiarize themselves with the trading process. It was made very clear that the training periods did not count for the final earnings.

After the training periods had ended, the specific instructions for the experiment were distributed. These instructions included information about the random process of the FV and about the final payments. Furthermore, it was pointed out that, after the last period, the experimenter would buy all shares. The price of this final transaction would equal the last CV of the shares. Subjects were invited to ask questions should anything be unclear.

Before the real market started, each subject had to confirm once again that they had read and understood the specific instructions by clicking a corresponding button on the screen. Then the market started and subjects began trading in 30 subsequent periods. After the last period had ended, socioeconomic data about the individuals was gathered by means of a questionnaire. Afterwards the subjects were paid in Euro. The conversion rate was 65 Talers/Euro. Each session lasted about 75 minutes. The instructions distributed to the agents are provided in appendix A.

4.3 Fundamentals and distribution

The CV only depends on past events, i.e. on the total number of periods where the good and the bad regime reigned. Apart from that, only a starting value is needed to calculate the CV. Let CV(t) denote the current value in period t (t = 1, …, T) and FV(t) the fundamental value in period t. The calculation of FV(t) is more complicated. It equals the expected CV in the last period, i.e. FV(t) = E[CV(T)].

When calculating FV(t), one has to take into account whether the good or the bad regime reigns in period t. Let $FV_{good}(t)$ denote the fundamental value in period t when the good regime reigns. Likewise, $FV_{bad}(t)$ denotes the fundamental when the bad regime is in place. The fundamental in period t is calculated as follows:

$$FV_{good}(t) = E[CV(T)] = 0.75 * 1.1 * CV(t) * \frac{FV_{good}(t+1)}{CV(t+1)} + 0.25 * 0.9 * CV(t) * \frac{FV_{bad}(t+1)}{CV(t+1)}$$

$$FV_{bad}(t) = E[CV(T)] = 0.25 * 1.1 * CV(t) * \frac{FV_{good}(t+1)}{CV(t+1)} + 0.75 * 0.9 * CV(t) * \frac{FV_{bad}(t+1)}{CV(t+1)}$$

Note that neither FV(t+1) nor CV(t+1) is known in period t, because it is the outcome of a random process. However, it is not necessary to know either variable. It suffices to know the ratio FV(t+1)/CV(t+1). By exploiting the fact that CV(T) = FV_{good}(T) = FV_{bad}(T) = FV(T) ⇔ FV(T)/CV(T) = 1 these ratios can be calculated by backwards induction. E.g. by inserting FV(T)/CV(T) = 1 one obtains that the ratio FV_{good}(T-1)/CV(T-1) = 1.05. All 60 ratios (30 for FV_{good} and 30 for FV_{bad}) are provided in table 7 in appendix C. With the use of these additional parameters, FV(t) is computable by simple insertion.

Figure 3 shows the distribution of the autocorrelated process over 30 periods. The horizontal axis denotes the absolute number of periods where the good regime (or, for symmetry reasons, the bad regime) reigns. The vertical axis indicates the relative probability.

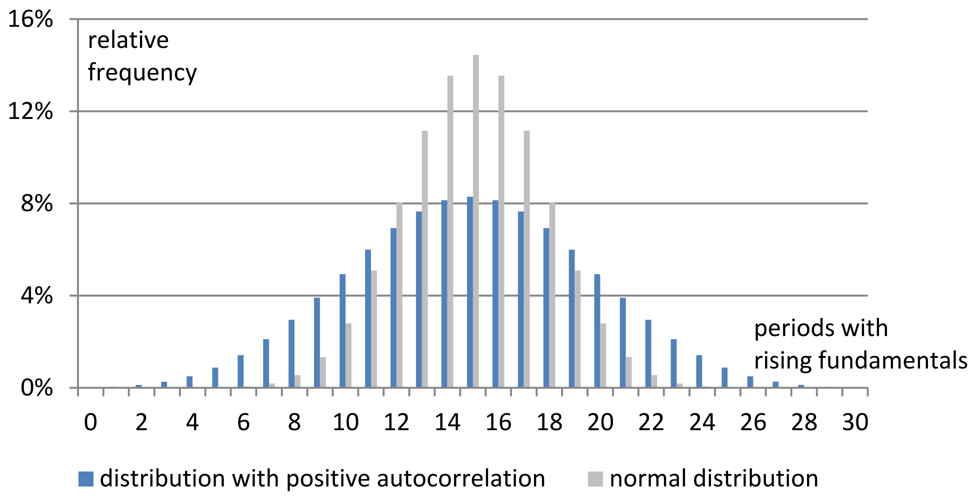

Figure 3: Relative frequencies of the regime type

The distribution with positive autocorrelation reflects the distribution of the stochastic process used in this experiment. For comparison, the normal distribution is given as well. It corresponds to a non-autocorrelated process, i.e. to a process where fundamentals rise or drop with a constant probability of 50% no matter what happened in the previous period. Both distributions are symmetrical to the balanced outcome of 15 times the good regime and 15 times the bad regime. The outcome of the symmetrical axis is the most probable outcome as well. However, compared to the normal distribution, extreme outcomes are more likely and balanced outcomes are less likely to occur in the autocorrelated process. This is due to the higher probability of long streaks. Whereas in the normal distribution one of the five most probable outcomes takes place with a cumulated probability of 64%, it only takes place with a probability of 40% in the distribution with positive autocorrelation.

4.4 Discussion of the design

Like every research method in general and every experimental design in particular, the one used in the present study has advantages and drawbacks. Section 4.4.1 highlights the strengths compared to previous designs and identifies new insights regarding asset markets which it may provide. Section 4.4.2 discusses weaknesses and problems.

4.4.1 Advantages

I investigate whether efficiency of an experimental asset market increases by using an intuitive design. Unlike Kirchler et al. (2012) I create an intuitive market for a stock of *an ordinary company,* not an intuitive market for the stock of *a depletable gold mine*. The FV of the stock of an ordinary company is neither constant nor continuously declining in this sense. It follows a random track and may rise or fall. A random walk is the image many people have in mind when they think of how stock prices change.

I refrain from providing a separate table specifying the FV and the expected dividend, because it might overburden some subjects to simultaneously observe both the trading screen and the table. Instead, all relevant information is provided on the screen. Another intuitive feature is that the FV in forthcoming periods is not known ex ante. Agents have to observe the outcome of the stochastic process and are expected to react accordingly.

The finding of Noussair & Powell (2009) that efficiency in experimental asset markets varies across time profiles of the fundamental is not easy to transfer to the real world. The time after a real stock has passed a local maximum (minimum) is typically also the time before it reaches a local minimum (maximum). In this sense it is unclear whether the track of a fundamental has to be partially attributed to the peak or to the valley treatment.

The design of the present experiment is likely to generate multiple peaks and valleys. I investigate whether the quality of price discovery differs when the fundamental temporarily rises or declines. A focus is on the turning points, because they are often good moments to trade. The stochastic process offers a possibility to check whether the asymmetry of trading behavior at these points (Noussair & Powell, 2009) is robust to a change of the design.

To test whether traders are prone to the GF or the HHF, it is advantageous that the FV fluctuates and is not known ex ante. The track of the CV is given on the trading screen. This visualization may help subjects form expectations regarding the future track.

One reason why there is so little research on the GF and the HHF in experimental asset markets may be that the fundamental in most of these markets declines continuously. This does not provide a good basis for analyzing the fallacies.

In principle, fluctuating dividends in the classical SSW design could also serve as a basis for investigating the GF and the HHF. For example, a large dividend in one period may raise the expectation that the subsequent dividend will be smaller. But the prevalent confusion among subjects is likely to distort results. A setup where confusion is low is conducive to investigating specific biased beliefs like the two most popular fallacies. I am not aware of any previous study examining the GF and the HHF an experimental asset market.

By providing a more intuitive and in some ways more realistic setup, I am not trying to "bring reality into the laboratory". The reduction of complexity is not only unavoidable but a crucial advantage of experimental economics. However, I argue that it should go hand in hand with a reduction of confusion. Earlier studies often fail to achieve this, possibly because it was not a major goal. I do not criticize this. Over the past two decades it has been shown that subjects who act in experimental asset markets are easily confused even when the setup seems simple.

While the setup is one of the first with stochastic fundamentals in an experimental asset market, I want to emphasize that this innovation is substantively motivated and not driven by the mere aim to try something new. I do find it surprising that for a quarter century of experimental research on asset markets, all fundamental processes followed a predetermined track, and it does seem worth repairing this status by giving another approach a chance.

However, the main aim of the setup is to improve intuitiveness of the market for subjects who confront it for the first time. This is all the more important because I consciously refrain from running the experiment only with students of economics or business administration in order to check whether the design facilitates efficiency even in the absence of a profound understanding of economics in general or personal experience with stocks in particular. Therefore, I chose a design without frequent dividend payments and without a continuously declining FV. Instead, the fundamental fluctuates with a random process. This is how many people picture the stock market.

It is not obvious how subjects behave in this new market. Some sources of confusion are eliminated and replaced by more intuitive features. However, subjects may conceivably be confused by one of the new elements which I did not regard as confusing. In any case, it is worth a try. Depending on the results of this study, it may provide new insights regarding asset markets or at least contribute to strengthening or weakening internal and external validity of previous studies.

The first CV is chosen to be 20 because this means that the FV in the first period is either 23.7 in the bad regime or 28.8 in the good regime, leading to a C/A ratio close to one in the first period. The value of all ten shares a subject possesses is roughly as high as the initial money endowment (250 Talers) of the subjects. The probability that a regime stays the same is chosen to be 75%. This makes the occurrence of longer streaks likely. The length of streaks is important for checking whether the HHF starts to dominate a trader´s decisions at some point. However, the higher the probability, the fewer peaks and valleys can be expected, and the more extreme outcomes are realized in the distribution. In the end, the 75% probability is a compromise between the length of the streaks and the number of turning points.

4.4.2 Drawbacks

The new design, though advantageous in many respects, also has some drawbacks. First of all, the nominal amount of money is constant, but the fundamental changes. This means that the cash/asset ratio is non-constant. It varies anti-proportionally with the fundamental. Depending on how far the FV departs from its initial value over the course of the experiment, the change of the C/A ratio can be substantial. However, with a certainty of more than 90% (99%), the C/A ratio neither increases by factor greater than 3.88 (8.65) nor decreases by a factor smaller than 0.35 (0.15) during the experiment. In the classical SSW treatment, the C/A ratio increases at least fifteenfold. This is the unlikely case when all dividend payments are zero.

Furthermore, a stochastic process of the FV may at first seem more complicated than one where it declines continuously or remains constant. However, as explained above, it is closer to intuitive images of a stock exchange. The experiment is the attempt to check whether the greater realism outweighs the greater complexity.

One specific characteristic which some agents might find hard to understand is the distinction between the FV and the CV. An efficient price equals the FV. However, it is conceivable that subjects pay more attention to the *current value.* They might think that what happens “currently” is more important than the expected value of the share after period 30. While some subjects might correctly focus on the FV, others might wrongly focus on the CV and others yet might think that an intermediate price is correct. To check for this, the questionnaire asks subjects whether they used the FV or the CV as a benchmark when they were trading.

New features of the design are the random process and the different regimes. This required some new instructions for the subjects. All in all, the modifications are quite substantial. If only one parameter had changed compared to other experimental asset markets, differences in outcome could have been attributed to this parameter. As it stands, differences in outcome could be caused by any one of the multiple new features, or by a combination of them.

Despite these drawbacks, the setup was chosen. Principally, it would be possible to hold the C/A ratio constant by introducing separate accounts (similar to Kirchler et al., 2012). But the procedure is complicated and likely to confuse subjects. The fluctuating FV may provide new insights into price discovery and the role of the GF and the HHF in asset markets. The simulated business cycle may seem more familiar to subjects than a random walk without any autocorrelation.

5 Results

Figure 4 shows the time series of median transaction prices and fundamentals by period. As mentioned above, each session includes two separate markets. Markets 1 & 2 (session A) feature the track of one fundamental and markets 3 & 4 (session B) feature the track of another. Both differ strongly from each other. The FV in session A regularly changes its direction. The FV in session B mostly increases. An increasing fundamental means that the good regime reigns. Overall, the results, shown in figure 4, indicate that:

- Price discovery in the associated markets within the sessions is similar, but differs across sessions;
- Price discovery is better in session A than in session B;
- Prices are less volatile than fundamentals.

Because price discovery in session A differs strongly from price discovery in session B, the following paragraphs summarize the main characteristics of each session.

Session A: Prices and fundamentals have the same direction in most periods. 45 times, the change of the fundamental and the change of the price share the same sign, i.e. both fundamentals and prices move in the same direction. Only 13 times does the sign differ, i.e. fundamentals and prices move in opposite directions.[9] Price discovery improves over the course of the experiment and is very good towards the end. In 20 (40) periods, the fundamental is below (above) the price.

Session B: There seems to be a strong anchoring effect. In the course of the experiment fundamentals increase sevenfold (700%). Prices are not even close to reflecting this. Up to period 27, prices only increase by around 23% and 20% respectively. Out of the 58 changes of the FV, the change of the price has the same sign 27 times and a different sign 31 times. No subject makes only beneficial trades, each one sells (buys) at least one share for a price below (above) the FV. In the last ten periods, only one subject makes no bad trades and acts rationally.[10] In both markets, end game effects are prevalent, although they differ in quality. In market 3 there is no trade at all in the last period. In market 4 prices increase fourfold (400%) in the last three periods. However, even in the last period, the price is still much

[9] For the experiment consists of 30 subsequent periods, there are 29 changes of the FV per market, i.e. 58 changes in each session.

[10] Several other subjects neither have money nor stocks towards the end. They are not regarded as rational traders. The fact that they lost all the money and stocks strongly indicates that they trade highly irrational.

lower than the fundamental. This is interesting, because it requires no backward induction to understand that the FV can no longer change. Thus, even if agents were only boundedly rational, the price and the fundamental should coincide at least in the last period.[11]

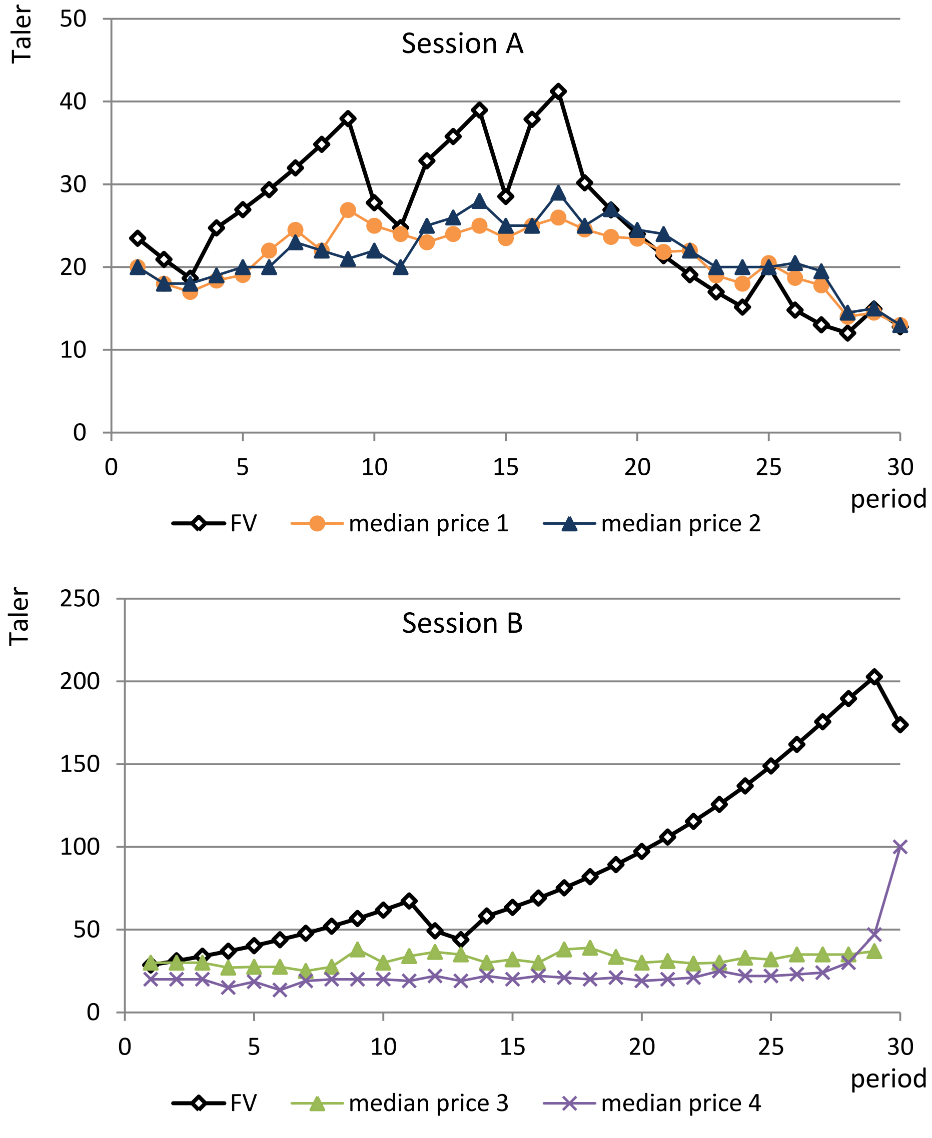

Figure 4: Fundamentals and median prices

In each of the two sessions, the sign of deviation between fundamentals and prices in the two associated markets is usually the same, i.e. if one of the two markets is overvalued or undervalued then so is the other. Price discovery is very good in the few periods where the sign is different. This leads to a negligible difference between mispricing and OV within both sessions. Therefore the following section concentrates on mispricing.

[11] The FV is always given to the subjects, i.e. subjects never have to make a backwards induction. However, with many periods left there may be more uncertainty prevalent than with no period left.

Figure 5 displays prices (dark blue line)[12] and confidence intervals of the FV. The horizontal axis denotes the period. The vertical axis denotes the fundamental and the price respectively. The 70% (95%) confidence interval means that there is a 70% (95%) probability that the final payout per share will be in the indicated range. Prices in session A are mostly within the 70% confidence interval. Only in the last periods, where the range gets small, do prices move outside the 70% interval. In session B, prices are in the 70% interval only for the first 15 periods. Because prices remain low while fundamentals increase markedly, from period 19 on prices are even outside the 95% confidence interval. Though not impossible, it is hard to imagine that sellers in session B trade for strategic considerations and speculate that prices will fall in future periods as described in section 2.4. More likely is the interpretation that at least the sellers fail to understand that the rational price equals the expected final buyout.

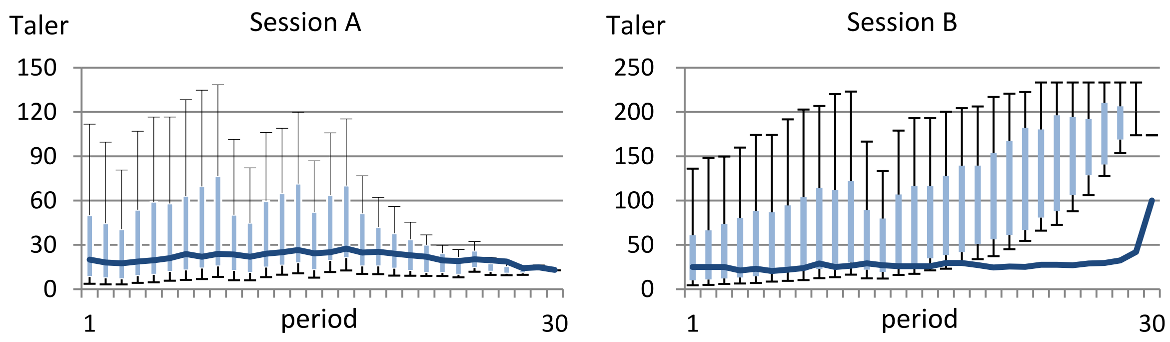

Figure 5: 70% (light blue) and 95% (grey) confidence intervals of the final buyout

Table 3 concerns mispricing. The rows include session A and session B. Additionally, two treatments of Kirchler et al.´s (2012) study are specified, namely the classical treatment and one with constant fundamentals. The values of these treatments serve as a baseline for comparing the amount of mispricing. Average mispricing in sessions A & B measures the mean mispricing in the associated markets across all periods. Maximum mispricing refers to one specific period.

There is ambiguous support for hypothesis 1. Mispricing within the sessions is lower than in the classical SSW treatment. However, it is very different across sessions. Whereas both average and maximum mispricing in session A is much lower than in the SSW treatment,

[12] The dark blue line is the arithmetic mean of median transaction prices in markets 1 & 2 and in markets 3 & 4 respectively.

average mispricing in session B is slightly higher. Still, maximum mispricing is lower. Both measurements of mispricing are by far the lowest in the reference treatment with constant fundamentals. This type of track of a fundamental seems to be more conducive to generating high efficiency than the design used in the present study.

	av. mispricing	max. mispricing
Session A	20.01	43.32
Session B	59.10	84.03
Classical[13]	57.16	140.00
Constant FV[14]	0.63	2.00

Table 3: Mispricing

The results indicate that the range within which fundamentals fluctuate is an important factor for mispricing. A high range as in the classical treatment and session B leads to significant mispricing. A smaller range, as realized in session A, induces less mispricing. Finally, a range of zero (constant fundamentals) minimizes mispricing. This may be explained by the creation of common expectations as proposed by Smith et al. (2000) and Cheung et al. (2012). Small fluctuations of the FV may promote common expectations and thereby improve efficiency.

It has to be mentioned that the usual way to measure mispricing has an inherent disadvantage. The *fundamental* serves as baseline. However, a change of perspective such that the price is regarded as baseline can influence results: To reach efficiency again, a given amount of mispricing requires a bigger price adjustment when the price is below fundamentals than when it is above fundamentals. E.g. an underpricing of 50% requires the price to double to reflect the fundamental correctly. By contrast, a price which is 50% above the fundamental only has to drop by one third to achieve this. The discrepancy of necessary price adjustments increases for large mispricings. This is especially relevant for the results of session B, where remarkable underpricing is prevalent. One could argue that a maximum UV of 84% is a bigger deviation from fundamentals than an OV of 140%. Nevertheless, for reasons of comparability I revert to the usual way of measuring mispricing (see Noussair & Powell, 2009; Kirchler et al., 2012).

[13] Classic SSW treatment: continuously declining FV and increasing C/A ratio; values from Kirchler et al. (2012), treatment 1.
[14] Constant FV and increasing C/A ratio; values from Kirchler et al. (2012), treatment 2.

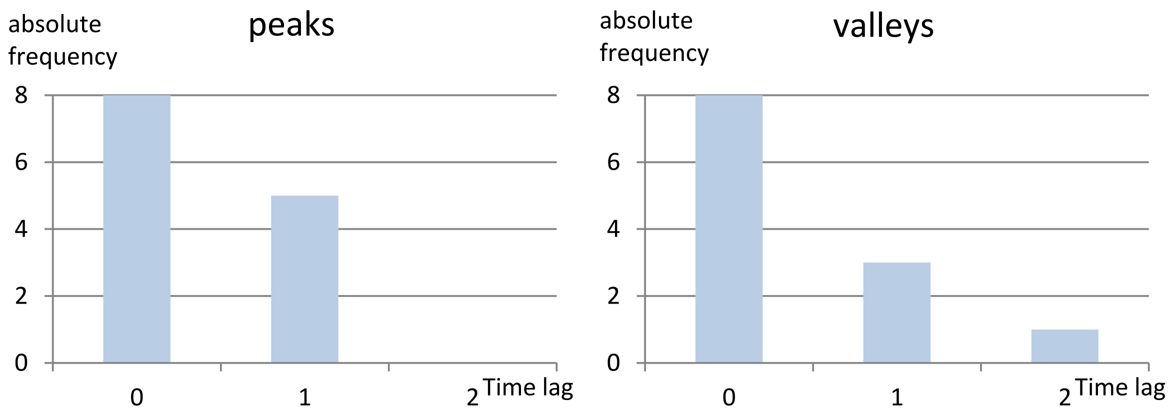

Figure 6: Time lags in peaks and valleys

Figure 6 shows the distribution of the time lags of price adjustments after peaks and valleys. The horizontal axis denotes the time lag. The vertical axis indicates the number of peaks and valleys respectively.[15] Let t_0 denote a period with an extreme point of fundamentals. The existence of an extreme point is not revealed until the fundamental changes direction. Therefore the price trend can reverse in response to a reversal of the fundamental in period (t_0+1) at the earliest. A time lag of length x (x = 0, 1, 2, …, X) is defined as the number of consecutive periods where prices and fundamentals move in opposite directions after an extreme point has been passed, i.e.: $\{[FV(t_0+x)/FV(t_0+1+x) > 1 \cap p(t_0+x)/p(t_0+1+x) < 1] \cup [FV(t_0+x)/FV(t_0+1+x) < 1 \cap p(t_0+x)/p(t_0+1+x) > 1]\}$.

	Modal time lag	Median time lag	Mean time lag
peaks	0	0	0.38
valleys	0	0	0.42
all extreme points	0	0	0.40

Table 4: Time lags in peaks and valleys

The results support hypothesis 2. Though there is a small mean time lag of 0.40 periods across peaks and valleys, both modal and median time lags equal zero. Prices revert to moving in the same direction as fundamentals no later than two periods after an extreme

[15] Number of peaks/valleys: 10 peaks is session A + 3 peaks in session B = 13 peaks (no trade after the last peak in market 3, therefore no price adjustment and no measureable time lag); 10 valleys in session A + 2 valleys in session B = 12 valleys. The time lags after the peaks are a lower bound: In market 4 directions of the FV and the price differ in the last period. In figure 2, the minimum time lag of 1 is assumed for this case.

point. Using a Mann-Whitney U test, the null hypothesis that the distribution of time lags is identical after peaks and valleys cannot be rejected at the 10% level.[16] This is not in line with Noussair & Powell (2009), where the time lag is systematically larger after valleys. Table 4 summarizes the time lags.

The expected time lag of two i.i.d time series with infinite periods equals[17]

$$\frac{1}{2} * \sum_{x=0}^{\infty} \frac{\mathrm{x}}{2^{\mathrm{x}}} = 0 + \frac{1}{4} + \frac{2}{8} + \frac{3}{16} + \frac{4}{32} + \cdots = 1.$$

Thus, the observed mean time lag of 0.40 is much lower and indicates that traders react to a trend reversal of the fundamental, even though no trader is completely rational (see above).

Trend discovery means that prices move in the same direction as fundamentals from one period to the next. The first two columns of table 5 show the fraction of it in both types of regimes. The last two columns contain the fraction of trend discovery directly after a peak or a valley. Trend discovery is much better in session A than in session B. Particularly, the discovery rate in session B is lower than 50%, which is the expected fraction of consistency of two independent processes.

Across both sessions, trend discovery is worse in the good regime than in the bad regime. This indicates that trends of underlying fundamentals impact trend discovery. While increasing fundamentals come along with increasing prices in only 56% of all cases, it is much more likely that prices follow the track of the fundamental when the fundamental declines (76%). However, these results are likely to be biased by session B, where prices are mostly increasing and trend discovery is very bad. More data is needed to check whether it is significant that prices are more likely to follow the direction of the fundamental when it is declining. After extreme points, trend discovery is better than it is during an average period where the good regime reigns, but it is worse than in an average period where the bad regime reigns. This is somewhat surprising because, due to the positive autocorrelation in its

[16] To run a Mann-Whitney U test, observations have to be independent from each other. This is definitely the case between extreme points in different markets. Some arguments also justify regarding peaks and valleys within each market as independent: The process is stochastic and cannot be influenced by anyone. The median transaction price is calculated for each single period. Therefore all available peaks and valleys are used to run the Mann-Whitney U test. However, it is possible that e.g. learning effects during the experiment or end game effects hamper independence of observations within markets. To solve this concern, more markets have to be run to obtain more definitely independent observations.

[17] With a probability of 50% the time lag is zero. With a probability of 25% the time lag is 1, this is the case when prices and fundamentals move in opposite directions in the period after the extreme point and in the same direction in the subsequent period. With a probability of 12.5% the time lag is 2 and so on.

process, the FV changes more markedly after an extreme point than after a non-extreme point (though, the CV always changes by 10% as described above). The *magnitude* of a change of the fundamental does not strongly affect trend discovery.

	Good regime	Bad regime	After peaks	After valleys
Session A	0.73	0.81	-	-
Session B	0.48	0.40	-	-
total	0.56	0.76	0.62	0.67

Table 5: Fraction of trend discovery

Hypothesis 3 concerns the impact of fallacious beliefs on trading behavior. A belief in the GF could result in underreaction to new information, a belief in the HHF in overreaction to new information. I relate median transaction prices to the FV. The dependent variable is the amount of OV (UV).

Let $streak_{rt}$ denote a streak of regime r (r = good, bad) in period t. A streak of length k is the number of consecutive periods with the same regime reigning. To check whether the length of a streak affects OV, $streak_{rt}$ is one independent variable. The effect of long streaks is measured by the second independent variable $streak_{rt}^2$. A switch from GF- to hot-hand beliefs would result in coefficients of $streak_{rt}$ and $streak_{rt}^2$ with opposite signs. Inspired by the interpretation of streaks of drawn Lotto numbers (Jørgensen et al., 2011) the length k of $streak_{rt}$ is defined as follows:

$streak_{rt} = k$ if regime r reigned in period t to (t-k+1) and not in period (t-k).

It is unobservable whether subjects assume the regime to change or to stay in the next period. However, observing their trading behavior allows some inferences about the underlying thoughts. The results of the regression of the linear model specified below might give some insights about subjects´ expectations and whether expectations follow specific mechanisms, e.g. the GF or the HHF. I interpret a price which is too high (low) as indication that traders overestimate the probability of rising (falling) fundamentals in the following periods.

$OV_{rt} = \beta_0 + \beta_1 * streak_{rt} + \beta_2 * streak_{rt}^2 + \varepsilon_t$

Figure 7 shows both streaks of the good and of the bad regime. On the horizontal axis the number of consecutive periods with the same regime is given, i.e. the length k of a streak.

The vertical axis indicates the absolute frequency. A streak of length k > 1 always has a preceding streak of length k-1. As streaks get longer, the absolute frequency gradually declines.

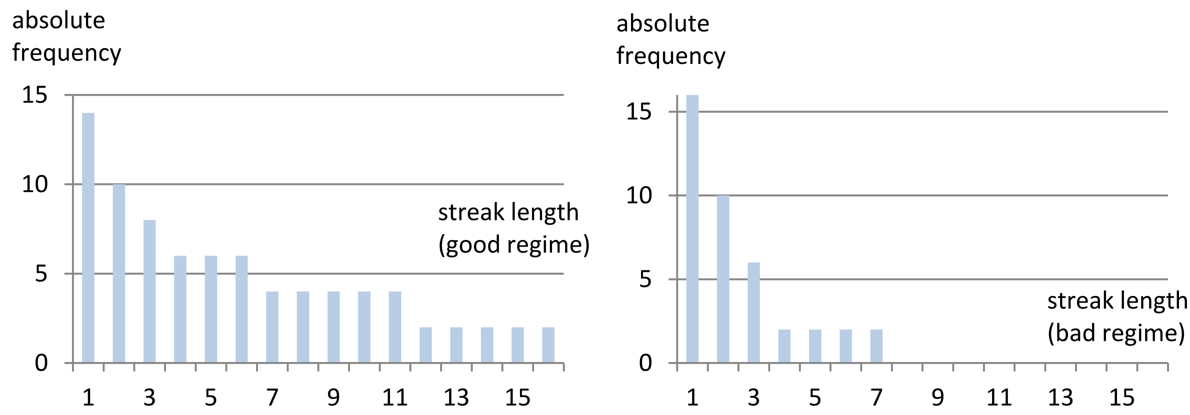

Figure 7: Streaks of the good regime and of the bad regime

Table 6 summarizes the most important results of the regression. Results indicate that agents tend to trade at too low prices when the good regime reigns. The longer a streak lasts, the higher is the amount of undervaluation. However, the coefficient of $streak_{good,t}^2$ indicates that the speed of increasing undervaluation slows down with longer streaks and might turn into a decrease of undervaluation and for very long streaks even into overvaluation eventually. This finding is in line with the idea that the HHF arises from the GF and that humans can be prone to both biases. Results are significant at the 1% level for the coefficient that measures the belief in the GF and significant at the 5% level for the hot-hand belief.

independent variable		coefficient	t	p>|t|	Adj. R^2
streaks of the good regime	constant	-16.22	-3.63	0.001	0.60
	$streak_{good,t}$	-7.69	-5.06	0.000	
	$streak_{good,t}^2$	0.22	2.23	0.028	
streaks of the bad regime	constant	-20.37	-1.81	0.078	0.18
	$streak_{bad,t}$	8.54	1.04	0.306	
	$streak_{bad,t}^2$	-0.33	-0.30	0.769	

Table 6: Results of the regressions

Though results are not significant for bad streaks, the sign of the coefficients point in the same direction: A streak of several consecutive periods with the bad regime reigning leads to increasing OV. Similar to the case with streaks of the good regime, the speed of increasing OV slows down with longer streaks. There are relatively few observations available to run the regression. With more data the results might become significant, indicating that GF and hot-hand beliefs exist in asset markets both in series of good and bad events.

Though some results are (highly) significant, some concerns remain. The first concern is whether the standard assumptions are met. Although, ideally, prices are formed anew each period regardless of prices in previous periods, it is conceivable that former prices do influence a trader´s behavior. This would violate the assumption that observations are independent from each other. The regression would be unfeasible. Solving this problem requires running a regression that uses only one specific streak length per market. For example, one observation would be OV when the streak length is k=1 in market 1 and another observation would be OV with k=2 in market 2. Via this procedure, the independence of observations can be guaranteed. However, because only a subset of all available observations would be used, more markets than in this study would have to be run to obtain enough independent observations.

The second concern regards the causal relevance of the GF for the observed outcomes. An achoring effect, which may also be present, leads to similar outcomes. Like the GF it also reduces volatility and tends to trigger OV in the bad regime and UV in the good regime. The estimated coefficient for the length of good streaks is strongly influenced by session B, where initial prices persist at very low levels while fundamentals increase considerably. It is possible that this is caused by a general lack of understanding rather than by a belief in the GF. Particularly, after period 21 in market 3 and after period 19 in market 4, prices are always below the theoretically possible final value of the shares, i.e. prices are below the value a share would have after the last period if the bad regime reigned uninterruptedly until the end. Believing in the GF or in the HHF alone cannot justify prices that are beyond the maximum or minimum final values.

The questionnaire suggests that most subjects failed to realize that the rational price of a share equals the expected buyout price. Though 94% of the subjects state that they understood the concept of the market “after a few periods in the real market” at the latest, they fail to identify the importance of the FV. Only 25% declare that the FV was their benchmark when they were offering or buying shares. The remaining subjects either used the CV as a benchmark (33%) or specified that they had no benchmark at all (42%). This is particularly disappointing because an important goal of the design was to observe subjects confronted with an asset market whose functionality is easier to understand than many previous experimental asset markets.

Almost 2/3 of all traders declare that their motivation for trading was to increase their final payment. Only a minority of 22% felt that the experimenter expected them to trade. This is positive because it suggests that the experimenter´s demand effect is not a major issue in the present study.

6 Discussion

6.1 Summary and critical review

I conducted an experimental double auction asset market designed to create a stock market environment familiar to agents. To simulate a business cycle with bull and bear markets, the market featured stochastic fundamentals and positive autocorrelation of changes in the value of the fundamental. By running this experiment, I continue along the path towards more realistic tracks of the FV, following Noussair et al. (2001) and Noussair & Powell (2009). Though advantageous in many respects, the new setup came at the cost of higher complexity.

Modifications to previous studies include a fluctuating cash/asset ratio, a stochastic and trending FV, a percentaged change of the FV and partly new instructions. Altogether, these modifications are quite substantial and make it hard to identify specific parameters that are responsible for differences in price or trend discovery compared to earlier experimental asset markets.

Results indicate that mispricing and the spread of fundamentals during the experiment are positively correlated. Mispricing in the present study is lower than in the classical SSW treatment, but higher than in treatments with constant fundamentals. Trend discovery is better in the bad regime (falling fundamentals) than in the good regime (rising fundamentals). Soon after fundamentals reach a turning point, the price also changes direction. There is no statistically significant difference of the time lag after peaks and valleys. This is not in line with Noussair & Powell (2009), where the time lag is systematically larger after valleys. In the present study, the time lag is always small. There is some evidence that an average subject is prone to the gambler´s fallacy. In the good regime, subjects tend to underprice the asset. The longer a streak lasts, the higher is the amount of underpricing. However, the speed of increasing undervaluation slows down, which might result in overpricing for very long streaks. This finding confirms the idea that the HHF may arise from the GF and that agents are prone to both fallacies. Though coefficients for streaks of the bad regime indicate the same behavior, i.e. an eventual slow down of the increase of OV, results are not significant in this case. This may be caused by the limited number of observations available for this study.

6.2 Outlook

The stochastic process of the FV proved useful to investigating the GF and the HHF. These fallacious beliefs have previously been studied in other settings, both in experiments (e.g. toss of a coin) and in the field (e.g. casino, lotto, stocks), but to my knowledge, mine is the first attempt to experimentally study their role in asset markets. Further experiments in this direction should maintain the stochastic process.

A major concern is that, in two of the four conducted markets, subjects failed to trade at prices close to the fundamental even in the final period. In the classical SSW treatment, where bubbles are typical phenomena, prices track fundamentals quite well towards the end of the experiment. To encourage more rational trading behavior, one could replace the percentaged rise and drop of the value of a share (± 10%) at the beginning of each period by a fixed change (e.g. ± 2 Talers). This would limit the possible range of the FV and might be easier to understand, thus helping subjects improve their performance at least in the last periods.

Furthermore, it turned out that most subjects failed to grasp the difference between the CV and the FV. A straightforward way to address this problem is to eliminate the difference. Abstaining from the positive autocorrelation, i.e. setting the probability of a regime switch to 50% would equalize the FV and the CV (see appendix C). I recommend trying this in future experiments.

Appendix A: Instructions for experiment

1. General Instructions

This is an experiment on decision making in a market. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money which will be given to you at the end of the experiment. The experiment consists of a sequence of trading periods in which you will have the opportunity to buy and sell in a market. The goods that can be bought and sold in the market are called Shares. The currency used in the market is taler. The cash payment to you at the end of the experiment will be in euros. The conversion rate is: 65 talers to 1 euro.

The experiment is organized as follows. First, everyone reads these instructions and participates in a practice period. Following the practice period, more instructions will be given, and then the real market will begin. Your earnings only depend on your actions in the real market. It will be made very clear when the real market begins.
In the end there will be a short questionnaire.

2. How to use the computerized market

Trading is conducted by making offers to buy and sell shares for talers. The screen is divided into 6 boxes (see picture).

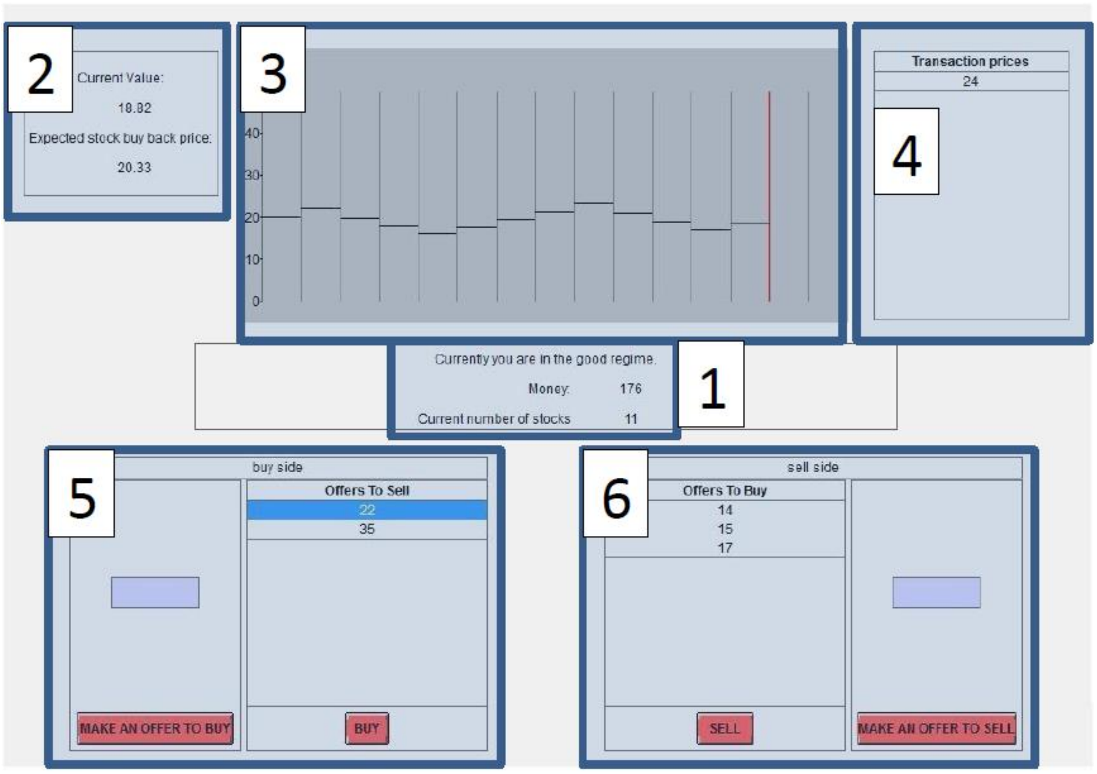

Figure 8: Trading screen of the subjects

BOX 1: INVENTORY AND CURRENT REGIME
The number of Shares and Money you currently have.
The regime of the current period: “good” or “bad”

BOX 2: “CURRENT VALUE” AND “EXPECTED STOCK BUY BACK PRICE”
After the last period you will sell all your remaining stocks to the experimenter for a price the stocks will have then. This is the “expected stock buy back price”.

BOX 3: TRACK RECORD OF THE “CURRENT VALUE”
The moving red bar indicates the time.

BOX 4: TRANSACTION PRICES
Prices of all transactions which took place in the current period. Once a new period starts, all transactions from the former period are deleted.

BOX 5: BUYING
Here you can "Make an offer to buy" a share, or "Buy" a share directly from someone who has offered to sell a share. When you buy a share, your amount of Money decreases by the price of the purchase.

To make an offer to buy, enter the price at which you are offering to buy a share, and then click the "Make an offer to buy" button. Your offer will now appear under "Offers to Buy" in the bottom-right of the screen (box 6).

To buy a share directly, click on an offer from the "Offers to Sell" list, then press "Buy". You will then buy one share for the currently selected price.

BOX 6: SELLING
Here you can "Make an offer to sell" a share, or "Sell" a share directly to someone who has offered to buy a share. When you sell a share your Money increases by the price of the sale.

To make an offer to sell, enter the price at which you are offering to sell a share, and then click the "Make an offer to sell" button. Your offer will now appear under "Offers to Sell" in the bottom-left of the screen (box 5).

To sell a share directly, click on an offer from the "Offers to Buy" list, then press "Sell". You will then sell one share for the currently selected price.

Your offers are always listed in blue. Submitting a second offer will replace your previous offer. If you have an offer selected and the offer gets changed, it will become deselected if the offer became worse for you. If the offer gets better, it will remain selected. It is not possible to borrow money or shares.

3. Practice Period

You will now have about 8 minutes to buy and sell shares in **practice** periods. Your actions in the practice periods do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have made offers to buy and offers to sell. Also be sure that you have accepted buy and sell offers.

If at any time you have any questions or concerns, the experimenter will come by and assist you.

4. Specific Instructions for this experiment

The experiment will consist of 30 trading periods, denoted by gray bars on the graphs. In each period, there will be a market open for 90 seconds in which you may buy and sell shares. Shares are assets with a life of 30 periods. Your inventory of shares and money carries over from one trading period to the next.
The current value of the shares rises or drops after each period by 10%.
There are two different regimes in the treatment – the "good" and the "bad" regime. The current regime is specified in box 1 of the trading screen (see above).

Properties of the **good** regime (in each period):

- The current value of the share **rises** by 10%.
- There is a **75%** probability that in the next period the **good regime will reign as well**.
- There is a **25%** probability that in the next period the **bad regime will reign**.

Properties of the **bad** regime (in each period):

- The current value of the share **drops** by 10%.
- There is a **75%** probability that in the next period the **bad regime will reign as well**.
- There is a **25%** probability that in the next period the **good regime will reign**.

In the very first period there is a 50:50 chance of starting in either the good or in the bad regime (see diagram). The current value in the first period is 20 talers.

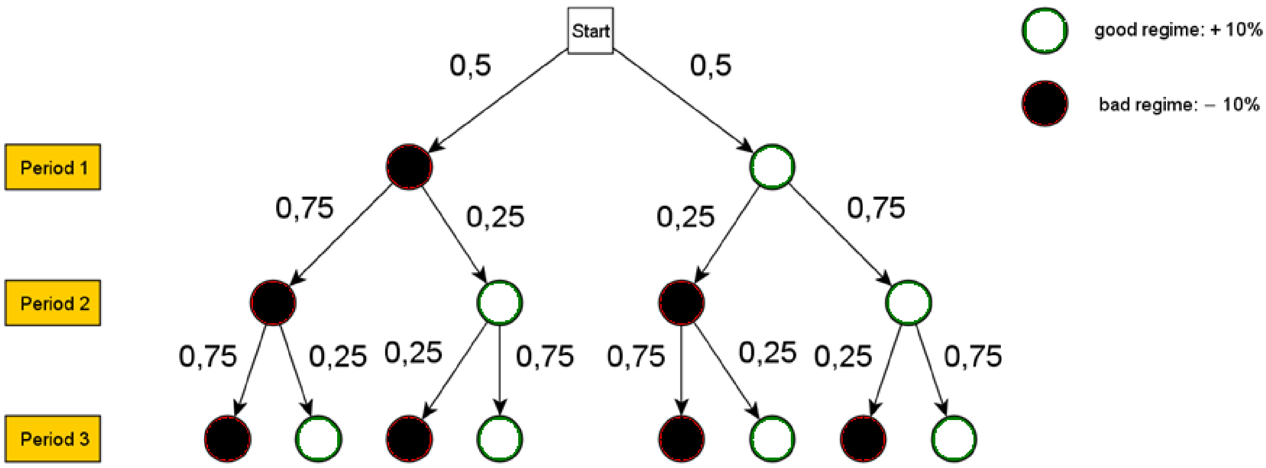

Figure 9: Stochastic process

Example: You are in period 14, the current value is 25 and you are in the good regime.
There is a 75% probability that in the next period (period 15) the good regime will reign as well. This would come along with a rise of the current value by 10% to 27.5 taler.
There is a 25% probability that in the next period (period 15) the regime will change to the bad state. This would come along with a drop of the current value by 10% to 22.5 taler.

When the last period is finished, the experimenter will buy all your remaining shares. The price will be determined by the current value the shares will have after the last period. The expected buy back price of the experimenter is specified in box 1 of the trading screen (see above). Note that this expected buy back price changes from period to period.

5. Your Earnings

Your earnings for the entire experiment will equal the amount of cash that you have at the end of period 30, after you sold your remaining stocks to the experimenter. The amount of cash you will have is equal to:

The cash (called “Money” on your screen) you have at the beginning of the experiment
+ money received from sales of shares
- money spent on purchases of shares

The conversion rate is: 65 talers to 1 euro.
Additionally, you get a show up fee of 5€.
The payment you receive will be rounded to the next 0.50 Cent.

Appendix B: Questionnaire

Gender:
- Male
- Female

Are you interested in the stock market?
- Very interested
- Rather interested
- Balanced
- Not so interested
- Not interested at all

Did you ever hold stock?
- Yes
- No

I would describe myself as
- Very risk averse
- Risk averse
- Risk neutral
- Risk loving
- Very risk loving

What do you think in which way your final payment did change due to your actions?
- My final payment increased by more than 20% due to my actions.
- My final payment increased between 10% and 20% due to my actions.
- My final payment changed in a range between +10% and -10%.
- My final payment decreased between 10% and 20% due to my actions.
- My final payment decreased by more than 20% due to my actions.

Why do you think you won/lost money with your actions during the experiment?
- Luck / Bad luck
- Skills
- I do not know

Did you use a benchmark for the price at which you traded the shares?
- The current value was my benchmark
- The expected buy back price was my benchmark
- I had no benchmark

What was the main reason for you to trade?
- Because I thougt I was expected to trade
- Because I wanted to earn more money
- I do not know

When did you understand the main concept of this market?
- I understood after reading the instructions
- I understood after the training periods
- I understood after a few periods in the real market
- I did not understand the concept until the end

Appendix C: Fundamental values and current values

period	FV(bad)/CV	FV(good)/CV
30	1,00	1,00
29	0,95	1,05
28	0,93	1,08
27	0,92	1,10
26	0,93	1,12
25	0,93	1,13
24	0,94	1,14
23	0,95	1,15
22	0,96	1,16
21	0,97	1,18
20	0,98	1,19
19	0,99	1,20
18	0,99	1,21
17	1,00	1,22
16	1,01	1,24
15	1,02	1,25
14	1,03	1,26
13	1,04	1,27
12	1,05	1,28
11	1,07	1,30
10	1,08	1,31
9	1,09	1,32
8	1,10	1,34
7	1,11	1,35
6	1,12	1,36
5	1,13	1,38
4	1,14	1,39
3	1,15	1,40
2	1,16	1,42
1	1,17	1,43

Table 7: FV/CV ratios per period

The FV/CV ratios of table 7 require a detailed explanation. This holds especially for the bad regime, where the value of the ratios has an interior minimal turning point in period 27. In contrast, the ratios of the good regime continuously decline as the final period approaches. Basically, the values indicate the factor by which the CV(t) has to be multiplied to obtain the expected final buyout, i.e. the FV(T) given that an agent is in the bad regime (middle column) or in the good regime (right column) in period t. Figure 8 shows the ratios in the good and in the bad regime for different regime switching probabilities (RSP). The probability of a regime switch is 25% in the present study and is depicted by the thick black line in the graph. The RSP is a parameter that should be varied in future experiments to get better insights on how this parameter affects efficiency and beliefs in the GF and the HHF, particularly the point where GF beliefs turn into HHF beliefs.

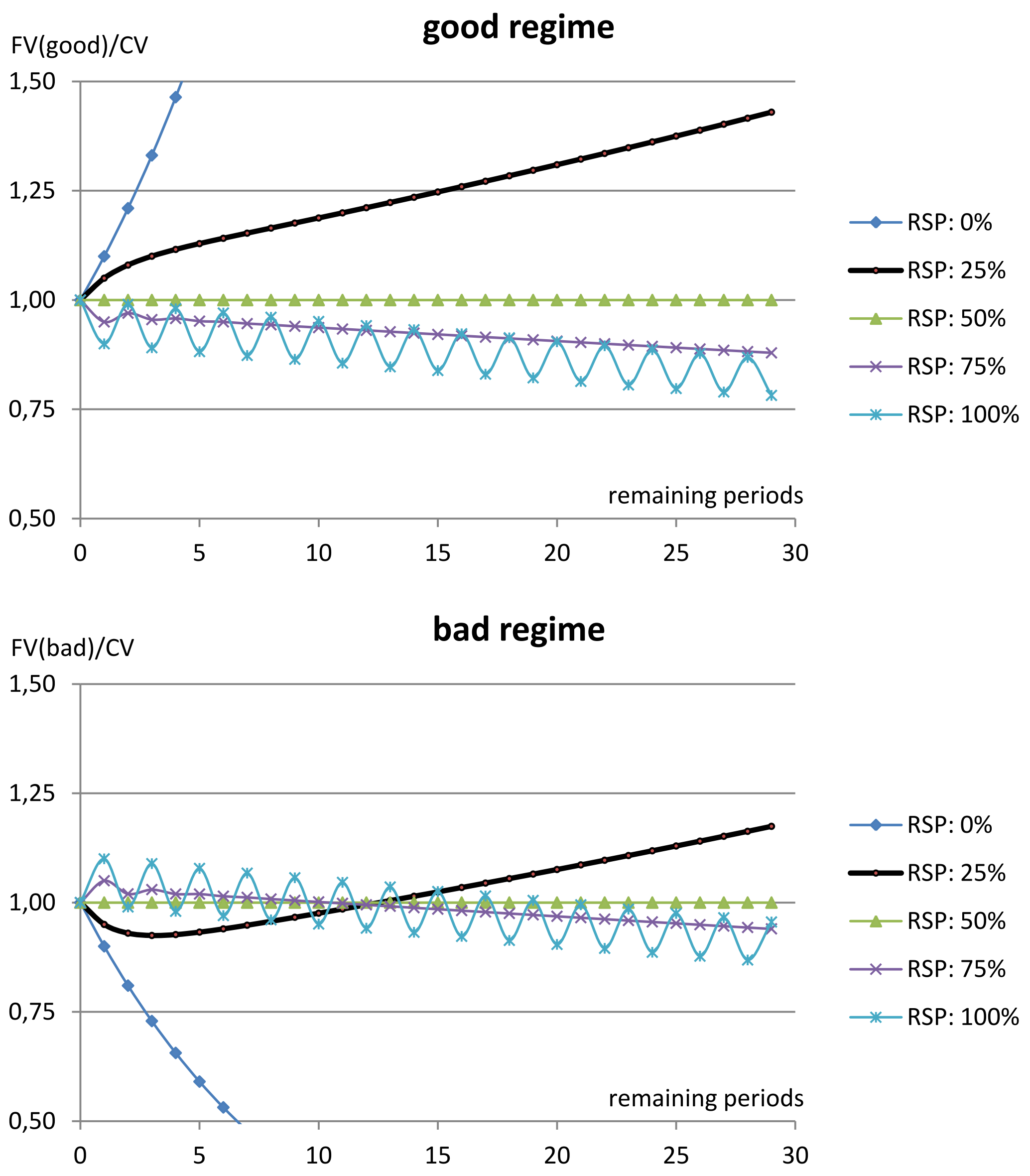

Figure 10: Ratios of FV/CV for different regime switching probabilities (RSP)

When no period remains, the FV/CV ratio is always 1, because the value of the final buyout is reached. It is evident that for both regimes the fundamental converges to zero for T $\rightarrow \infty$

and for high RSP (light blue and purple lines). A share which initially rises by 10% and subsequently declines by 10% will end at a lower level than where it started from: 1.1*0.9 < 1. These rises and drops lead to the sinuous shaped line: When the good (bad) regime reigns and there is only one period left, the bad (good) regime is likely to reign the in the final period, causing the asset value to drop (rise). When there are two periods left, it is likely that the value will both rise and drop. If this is repeated infinitely often, the final value converges to zero.

However, if the RSP decreases to 50% (this is the case with no autocorrelation), then the CV and the FV coincide in every period. Imagine there are two periods to go and the agent is in either type of regime: There is a 25% probability that the good regime will reign in both remaining periods and a 25% probability that the bad one will reign in both periods. The probability that there is a rise in one and a drop in the other period is 50%. This leads to the equation $0.25*0.9^2 + 0.5*0.9*1.1 + 0.25*1.1^2 = 1$. Regardless how many periods remain, the factor is always 1.

For low RSP, as realized in the present study, the probability of long streaks is high enough to let the FV/CV ratio go to infinity for $T \rightarrow \infty$, regardless which regime reigns in period t. This is due to the exponential growth in case of rising fundamentals. However, if there are only few periods to go and the bad regime reigns, there may be not enough periods left to make the turn around by switching the regime. The basic idea behind this mechanism is that streaks of the good regime lead to an exponentially speeding up of the CV, while streaks of the bad regime lead to slowing down of the drop of the CV as it converges to zero. When the probability of long streaks rises, the expected final payout increases. When a sufficient number of periods remain, the crucial parameter is the RSP and not the regime type in period t. The only exception is the case of perfect positive autocorrelation, i.e. RSP = 0%. In that case, the value is either always rising (good regime in t) or always dropping (bad regime in t).

The following equations summarize the possible realizations.

$$\lim_{T\to\infty} \frac{FV_{good}(t)}{CV(t)} = \begin{cases} \infty & if\ 0\% \leq RSP < 50\% \\ 1 & if\ RSP = 50\% \\ 0 & if\ 50\% < RSP \leq 100\% \end{cases}$$

$$\lim_{T\to\infty}\frac{FV_{bad}(t)}{CV(t)} = \begin{cases} 0 & if\ RSP = 0\% \\ \infty & if\ 0\% < RSP < 50\% \\ 1 & if\ RSP = 50\% \\ 0 & if\ 50\% < RSP \leq 100\% \end{cases}$$

Appendix D: Mann-Whitney U test

rank	time lag	peak/valley	median rank
1	0	peak	8.5
2	0	peak	8.5
3	0	peak	8.5
4	0	peak	8.5
5	0	peak	8.5
6	0	peak	8.5
7	0	peak	8.5
8	0	peak	8.5
9	0	valley	8.5
10	0	valley	8.5
11	0	valley	8.5
12	0	valley	8.5
13	0	valley	8.5
14	0	valley	8.5
15	0	valley	8.5
16	0	valley	8.5
17	1	peak	20.5
18	1	peak	20.5
19	1	peak	20.5
20	1	peak	20.5
21	1	peak	20.5
22	1	valley	20.5
23	1	valley	20.5
24	1	valley	20.5
25	2	valley	25.0

H_0: peaks and valleys belong to the same population

$n_{peak} = 13$; $R_{peak} = 8*8.5 + 5*20.5 = 170.5$

$n_{valley} = 12$; $R_{valley} = 8*8.5 + 3*20.5 + 25 = 154.5$

$U_{peak} = n_{peak}*n_{valley} + 0.5*n_{peak}(n_{peak} + 1) - R_{peak} = 76.5$

$U_{valley} = n_{peak}*n_{valley} + 0.5*n_{valley}(n_{valley} + 1) - R_{valley} = 79.5$

Min(U) = 76.5 > 41 = U(crit) → cannot reject H_0

Appendix E: z-Tree program code

```
zTree - [Master Thesis Experiment.ztt]
File  Edit  Treatment  Run  Tools  View  ?
Background
    factors
    saved_cvalues
    saved_contracts
    globals
    subjects
    contracts
    summary
    saved_contracts.do { ... }
        if (\Period == 1) {
         p = -1;
         timeCancelled = -1;
        }
    globals.do { ... }
        // --------- INITIALIZE VARIABLES ----------------
        TimeAuction = 90; // time per period.
        TimeProfit = -1; // time to display the profit screen, indefinitely = -1.
        NumPeriods = 30;
        TotalSeconds = TimeAuction * NumPeriods;
        ProbChange = 0.25; // Probability of a change of Regime
        StartCValue = 20;
        MultUp = 1.1; // multiplication factor if in good regime
        MultDown = 0.9; // multiplication factor if in bad regime

        // variables for plot
        Y_AXIS_OFFSET = 90;
        LABEL_OFFSET_ABOVE = 10;
        LABEL_OFFSET_BELOW = 5;
        NUM_SUBJECTS = 9;
        Y_MIN = 0;
        Y_MAX = 100;
        // introduce regimes
        CValue= -1;
        if(Period<=1){RegimeType=0;}

        secondCount = 1;
        secondTotal = 0;
    subjects.do { ... }
        InitialMoney = 250;
        InitialStock = 10;
        Money = 0;
        Stock = 0;
    contracts.do { ... }
        // set all variables to default values
        Seller = -1;
        Buyer = -1;
        Group = -1;
        Traded =0;
        contractID = 0;
        tradeID = 0;
        timeMade = -1;
        timeCancelled = -1;
        p = -1;
    Active screen
        header
    Waitingscreen
        texts
            Please wait for the experimenter
BeforeStart =|= (-1)N
    subjects.do { ... }
        Participate = if(Period==1, 1, 0);
```

```
Active screen
    Start
        Now you get further instructions for the experiment. Please click the "OK" button after you have read and understoo
        OK
Waitingscreen
Auction =|= (TimeAuction-1)A
    subjects.do { ... }
        Participate = if(Period>NumPeriods, 0, 1);
    globals.do { ... }
        // ------------------ LOOP --------------------------------
        secondTotal = (Period-1)*TimeAuction;
        // every "secondCount" seconds ...
        later( secondCount ) repeat {
           secondTotal = secondTotal + 1;
        }

        numContracts = 0;
        numTrades = 0;

        tp = 0;
        tSubject = 0;
        tcontractID = 0;
        tGroup = 0;
        tBuyer = 0;
        tinitialCID = 0;
        ttimeMade = -1;
        lowest_p = 10001;
        lowest_CID = 0;
        previous_p = 10001;
        previous_CID = 0;
        zp = 0;
        zSubject = 0;
        zcontractID = 0;
        zGroup = 0;
        zSeller = 0;
        zinitialCID = 0;
        ztimeMade = -1;
        highest_p = -1;
        highest_CID = 0;
        zprevious_p = -1;
        zprevious_CID = 0;
    subjects.do { ... }
        Money = if( Period <= 1, InitialMoney, OLDsubjects.find( Subject == :Subject, Money)) ;
        Stock = if( Period <= 1, InitialStock, OLDsubjects.find( Subject == :Subject, Stock ));

        StartMoney =  if( Period == 1, 0, Money);
    globals.do { ... }
        //Regime changing mechanism and current value calculator
        rand = random();

        RegimeType = if(OLDglobals.find(RegimeType) == 0 ,
        if(rand<= ProbChange, 1, 0 ) ,
        if(rand<= ProbChange, 0, 1));

        OldCValue = OLDglobals.find(CValue);

        CValue = if(Period == 1, StartCValue,
        if(RegimeType == 0, round( OldCValue * MultDown, 0.01),  round( OldCValue * MultUp, 0.01))
        );

```

```
globals(Period ==1).do { ... }
    expFValue = if(RegimeType==0, round(1.17440* CValue, 0.01), round(1.42981*CValue,0.01));
globals(Period ==2).do { expFValue = if(RegimeType==0, round(1.16299* CValue, 0.01), round(1.41592*CValue,0.01)); }
globals(Period ==3).do { expFValue = if(RegimeType==0, round(1.15170* CValue, 0.01), round(1.40217*CValue,0.01)); }
globals(Period ==4).do { expFValue = if(RegimeType==0, round(1.14051* CValue, 0.01), round(1.38855*CValue,0.01)); }
globals(Period ==5).do { expFValue = if(RegimeType==0, round(1.12943* CValue, 0.01), round(1.37506*CValue,0.01)); }
globals(Period ==6).do { expFValue = if(RegimeType==0, round(1.11846* CValue, 0.01), round(1.36171*CValue,0.01)); }
globals(Period ==7).do { expFValue = if(RegimeType==0, round(1.10760* CValue, 0.01), round(1.34848*CValue,0.01)); }
globals(Period ==8).do { expFValue = if(RegimeType==0, round(1.09684* CValue, 0.01), round(1.33539*CValue,0.01)); }
globals(Period ==9).do { expFValue = if(RegimeType==0, round(1.08619* CValue, 0.01), round(1.32242*CValue,0.01)); }
globals(Period ==10).do { expFValue = if(RegimeType==0, round(1.07564* CValue, 0.01), round(1.30957*CValue,0.01)); }
globals(Period ==11).do { expFValue = if(RegimeType==0, round(1.06519* CValue, 0.01), round(1.29685*CValue,0.01)); }
globals(Period ==12).do { expFValue = if(RegimeType==0, round(1.05485* CValue, 0.01), round(1.28426*CValue,0.01)); }
globals(Period ==13).do { expFValue = if(RegimeType==0, round(1.04460* CValue, 0.01), round(1.27179*CValue,0.01)); }
globals(Period ==14).do { expFValue = if(RegimeType==0, round(1.03446* CValue, 0.01), round(1.25943*CValue,0.01)); }
globals(Period ==15).do { expFValue = if(RegimeType==0, round(1.02441* CValue, 0.01), round(1.24720*CValue,0.01)); }
globals(Period ==16).do { expFValue = if(RegimeType==0, round(1.01447* CValue, 0.01), round(1.23508*CValue,0.01)); }
globals(Period ==17).do { expFValue = if(RegimeType==0, round(1.00462* CValue, 0.01), round(1.22309*CValue,0.01)); }
globals(Period ==18).do { expFValue = if(RegimeType==0, round(0.99487* CValue, 0.01), round(1.21120*CValue,0.01)); }
globals(Period ==19).do { expFValue = if(RegimeType==0, round(0.98523* CValue, 0.01), round(1.19942*CValue,0.01)); }
globals(Period ==20).do { expFValue = if(RegimeType==0, round(0.97571* CValue, 0.01), round(1.18774*CValue,0.01)); }
globals(Period ==21).do { expFValue = if(RegimeType==0, round(0.96633* CValue, 0.01), round(1.17614*CValue,0.01)); }
globals(Period ==22).do { expFValue = if(RegimeType==0, round(0.95714* CValue, 0.01), round(1.16458*CValue,0.01)); }
globals(Period ==23).do { expFValue = if(RegimeType==0, round(0.94825* CValue, 0.01), round(1.15300*CValue,0.01)); }
globals(Period ==24).do { expFValue = if(RegimeType==0, round(0.93986* CValue, 0.01), round(1.14125*CValue,0.01)); }
globals(Period ==25).do { expFValue = if(RegimeType==0, round(0.93241* CValue, 0.01), round(1.12904*CValue,0.01)); }
globals(Period ==26).do { expFValue = if(RegimeType==0, round(0.92678* CValue, 0.01), round(1.11578*CValue,0.01)); }
globals(Period ==27).do { expFValue = if(RegimeType==0, round(0.92475* CValue, 0.01), round(1.10025*CValue,0.01)); }
globals(Period ==28).do { expFValue = if(RegimeType==0, round(0.93000* CValue, 0.01), round(1.08000*CValue,0.01)); }
globals(Period ==29).do { expFValue = if(RegimeType==0, round(0.95000* CValue, 0.01), round(1.05000*CValue,0.01)); }
globals(Period ==30).do { expFValue = if(RegimeType==0, round(1.00000* CValue, 0.01), round(1.00000*CValue,0.01)); }
globals.do { saved_cvalues.new{ ... }
Active screen
    CValue
        Current Value:
        : OUT( CValue )
        Expected stock buy back price:
        : OUT( expFValue )
    Trade
        Shares
            <>Currently you are in the <RegimeType|!text:1="good ";0="bad ";>regime.
            Money:: OUT( Money )
            Current number of stocks: OUT( Stock )
        buyside
            buy side
        make offer to buy: contracts
            : IN( p )
            MAKE AN OFFER TO BUY
                Money >= p
                contracts(Buyer).do { ... }
                    // Count the new contract.
                    \numContracts = \numContracts +1;

                    // Create the new contract, temporarily.
                    \zp = p;
                    \zSubject = :Subject;
                    \zcontractID = \numContracts;
                    \zGroup = :Group;
                    \zSeller = -2;
```

```
\zinitialCID = \numContracts;
\ztimeMade = secondTotal;

p = \zp;
Buyer = \zSubject;
Seller = \zSeller;
Maker = \zSubject;
Group = \zGroup;
contractID = \zcontractID;
Traded =0;
initialCID = \zinitialCID;
timeMade = \ztimeMade;

// Find the lowest previous contract, if it exists.
// Find the previous contract, if it exists.
\highest_CID = 0;
\highest_p = -1;
\zprevious_CID = 0;
contracts.do {
  if ( Seller == -1 & p > \highest_p ) {
    \highest_p = p;
    \highest_CID = contractID;
  }
  if (Maker == \zSubject & Seller == -1) {
      \zprevious_p = p;
      \zprevious_CID = contractID;
  }
}
Seller = -1;
\zSeller = -1;

contracts.do {
  // If a previous contract exists, eliminate it.
  if (\zprevious_CID == contractID) {
    Seller = -2;
  }
  // If the new contract is a new low,
  // switch the previous low with the new.
  if (\highest_CID == contractID & \zp > \highest_p) {
      // temp = lowest
      \zp = p;
      \zSubject = Buyer;
      \zGroup = Group;
      \zSeller = Seller;
      \zinitialCID = initialCID;
      \ztimeMade = timeMade;
      // lowest = new
      p = :p;
      Buyer = ::Subject;
      Maker = ::Subject;
      Group = ::Group;
      Seller = -1;
      initialCID = numContracts;
      timeMade = secondTotal;
  }
}

p = \zp;
```

```
Buyer = \zSubject;
Seller = \zSeller;
Maker = \zSubject;
Group = \zGroup;
contractID = \zcontractID;
Traded =0;
initialCID = \zinitialCID;
timeMade = \ztimeMade;
offers to sell: contracts( (Group == :Group ) & ( Buyer == -1 ) ), sorted by: p; -contractID
  Offers To Sell: OUT( p )
  BUY
    Seller != :Subject
    Buyer == -1
    Money >= p
    contracts.do { Buyer = :Subject; ... }
sellside
  sell side
offers to buy: contracts( (Group == :Group ) & ( Seller == -1 ) ), sorted by: p; -contractID
  Offers To Buy: OUT( p )
  SELL
    Buyer != :Subject
    Seller == -1
    Stock >= 1
    contracts.do { ... }
      Seller = :Subject;

      \numTrades = \numTrades +1;
      tradeID = \numTrades ;
      Traded =1;
      :Money = : Money + p;
      :Stock = : Stock -1;
      subjects.do{
       if ( :Buyer == Subject ) {
          Money = Money -:p;
          Stock = Stock +1;
       }
      }


      subjects.do{
          Price = :p;
      }

      contracts.do {
       if ( Seller == :Seller & Buyer == -1 ) {
          Buyer = -2;
       }
       if ( Seller == -1 & Buyer == :Buyer ) {
          Seller = -2;
       }
      }

      timeCancelled = secondTotal;
      saved_contracts.new {
         p = :p;
         timeCancelled = :timeCancelled;
      }
make offer to sell: contracts
  : IN( p )
```

```
MAKE AN OFFER TO SELL
  Stock>=1
  contracts(Seller).do { ... }
    // Count the new contract.
    \numContracts = \numContracts +1;

    // Create the new contract, temporarily.
    \tp = p;
    \tSubject = :Subject;
    \tcontractID = \numContracts;
    \tGroup = :Group;
    \tBuyer = -2;
    \tinitialCID = \numContracts;
    \ttimeMade = secondTotal;

    // Don't know why we need this, but anyway.
    p = \tp;
    Seller = \tSubject;
    Buyer = \tBuyer;
    Maker = \tSubject;
    Group = \tGroup;
    contractID = \tcontractID;
    Traded =0;
    initialCID = \tinitialCID;
    timeMade = \ttimeMade;

    // Find the lowest previous contract, if it exists.
    // Find the previous contract, if it exists.
    \lowest_CID = 0;
    \lowest_p = 10001;
    \previous_CID = 0;

    contracts.do {
     if ( Buyer == -1 & p < \lowest_p ) {
      \lowest_p = p;
      \lowest_CID = contractID;
     }
     if (Maker == \tSubject & Buyer == -1) {
       \previous_CID = contractID;
     }
    }

    Buyer = -1;
    \tBuyer = -1;

    contracts.do {
     // If a previous contract exists, eliminate it.
     if (\previous_CID == contractID) {
      Buyer = -2;
     }
     // If the new contract is a new low,
     // switch the previous low with the new.
     if (\lowest_CID == contractID & \tp < \lowest_p) {
       // temp = lowest
       \tp = p;
       \tSubject = Seller;
       \tGroup = Group;
       \tBuyer = Buyer;
       \tinitialCID = initialCID;
       \ttimeMade = timeMade;
```

```
p = :p;
Seller = ::Subject;
Maker = ::Subject;
Group = ::Group;
Buyer = -1;
initialCID = numContracts;
timeMade = secondTotal;
}
}

p = \tp;
Seller = \tSubject;
Buyer = \tBuyer;
Maker = \tSubject;
Group = \tGroup;
contractID = \tcontractID;
Traded =0;
initialCID = \tinitialCID;
timeMade = \ttimeMade;
History: contracts( (Group == :Group) & (Seller >0 ) & ( Buyer > 0) ), sorted by: tradeID
Transaction prices: OUT( p )
graph [1,TotalSeconds + Y_AXIS_OFFSET]x[Y_MIN - LABEL_OFFSET_BELOW,Y_MAX + LABEL_OFFSET_ABOVE]
EOP2: 30*TimeAuction + Y_AXIS_OFFSET,Y_MIN->30*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 29*TimeAuction + Y_AXIS_OFFSET,Y_MIN->29*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 28*TimeAuction + Y_AXIS_OFFSET,Y_MIN->28*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 27*TimeAuction + Y_AXIS_OFFSET,Y_MIN->27*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 26*TimeAuction + Y_AXIS_OFFSET,Y_MIN->26*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 25*TimeAuction + Y_AXIS_OFFSET,Y_MIN->25*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 24*TimeAuction + Y_AXIS_OFFSET,Y_MIN->24*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 23*TimeAuction + Y_AXIS_OFFSET,Y_MIN->23*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 22*TimeAuction + Y_AXIS_OFFSET,Y_MIN->22*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 21*TimeAuction + Y_AXIS_OFFSET,Y_MIN->21*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 20*TimeAuction + Y_AXIS_OFFSET,Y_MIN->20*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 19*TimeAuction + Y_AXIS_OFFSET,Y_MIN->19*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 18*TimeAuction + Y_AXIS_OFFSET,Y_MIN->18*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 17*TimeAuction + Y_AXIS_OFFSET,Y_MIN->17*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 16*TimeAuction + Y_AXIS_OFFSET,Y_MIN->16*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 15*TimeAuction + Y_AXIS_OFFSET,Y_MIN->15*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 14*TimeAuction + Y_AXIS_OFFSET,Y_MIN->14*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 13*TimeAuction + Y_AXIS_OFFSET,Y_MIN->13*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 12*TimeAuction + Y_AXIS_OFFSET,Y_MIN->12*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 11*TimeAuction + Y_AXIS_OFFSET,Y_MIN->11*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 10*TimeAuction + Y_AXIS_OFFSET,Y_MIN->10*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 9*TimeAuction + Y_AXIS_OFFSET,Y_MIN->9*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 8*TimeAuction + Y_AXIS_OFFSET,Y_MIN->8*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 7*TimeAuction + Y_AXIS_OFFSET,Y_MIN->7*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 6*TimeAuction + Y_AXIS_OFFSET,Y_MIN->6*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 5*TimeAuction + Y_AXIS_OFFSET,Y_MIN->5*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 4*TimeAuction + Y_AXIS_OFFSET,Y_MIN->4*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 3*TimeAuction + Y_AXIS_OFFSET,Y_MIN->3*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP2: 2*TimeAuction + Y_AXIS_OFFSET,Y_MIN->2*TimeAuction + Y_AXIS_OFFSET,Y_MAX
EOP1: 1*TimeAuction + Y_AXIS_OFFSET,Y_MIN->1*TimeAuction + Y_AXIS_OFFSET,Y_MAX
prices: y(Y_AXIS_OFFSET)
ticker: secondTotal + Y_AXIS_OFFSET,Y_MIN->secondTotal + Y_AXIS_OFFSET,Y_MAX
prices: graph: saved_cvalues( TRUE )
(Period-1)*TimeAuction + Y_AXIS_OFFSET,savedCValue->(Period)*TimeAuction + Y_AXIS_OFFSET,savedCValue
Waitingscreen
Results =|= (30)A
subjects.do { ... }
Participate = if(Period==NumPeriods, 1, 0);
```

```
subjects.do { ... }
    // Repurchase of stocks
    StocksEnd = Stock;
    if(Period==NumPeriods){
    Money = (OLDsubjects.find( Subject == :Subject, Money) + Stock * CValue);
    Stock = 0;
    }
Active screen
  Results
    Your holdings at the end of the experiment:
    Stocks: OUT( StocksEnd )
    Money: OUT( StartMoney )

    Stocks sold to the experimentator at a price of: OUT( CValue )
    Your money after selling all your stocks:: OUT( Money )
    Your payment in Euros:: OUT( 5 + Money/65 )

    Please wait. The questionnaire will start soon.
Waitingscreen
```

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Abstract

Die Fundamentalwerte gehandelter Wertpapiere entwickelten sich in der Geschichte von Marktexperimenten hin zu natürlicheren Verläufen -von gleichmäßig fallend über konstant bleibend bis hin zu schwankend. Die vorliegende Arbeit ist der nächste Schritt in dieser Richtung. Der Verlauf der Fundamentalwerte ist stochastisch. Um Bullen- und Bärenmärkte zu simulieren, werden zusätzlich verschiedene Grundzustände eingeführt. Stochastische Fundamentalwerte bieten die einzigartige Gelegenheit, die gamber´s fallacy und die hot-hand fallacy sowie die Verbindung dieser Täuschungen im Rahmen eines Marktexperiments zu untersuchen. Außerdem wird mit dem Experiment die Robustheit der Resultate früherer Studium überprüft. Die Ergebnisse zeigen, dass ein intuitives Design nicht ausreicht, um eine effiziente Preisfindung sicherzustellen. Verglichen mit Experimenten, in denen der Fundamentalwert gleichmäßig fällt, sind die Preise zwar näher am Fundamentalwert. Die größte Übereinstimmung von Preisen und Fundamentalwerten wird jedoch bei gleich bleibenden Fundamentalwerten erreicht. Obwohl nicht alle Ergebnisse statistisch signifikant sind, werden grundsätzlich die Resultate vieler Feldstudien bestätigt. Demnach ist es möglich, den Markt zu schlagen, wenn Aktien nach positiven Nachrichten gekauft und nach negativen verkauft werden. Nur nach sehr langen Phasen positiver bzw. negativer Nachrichten beginnen die Marktteilnehmer entsprechend der hot-hand fallacy zu agieren.

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