Multi-Asset Market Dynamics*

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Abstract

This paper explores multi-asset market dynamics. We consider a limited number of markets on which two types of agents are active. Fundamentalists specialize in a certain market to gather expertise. Chartists may switch between markets since they use simple extrapolative methods. Specifically, chartists prefer markets which display price trends but which are not too misaligned. The interaction between the traders causes complex dynamics. Even in the absence of random shocks, our artificial markets mimic the behavior of actual asset markets closely. Our model also offers reasons for the high degree of comovements in stock prices observed empirically.

JEL classification

D84, G12

Keywords

heterogeneous agents, technical and fundamental analysis, asset price dynamics, comovements in stock prices

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1 Introduction

By showing that the act of trading may create excess volatility, the chartist-fundamentalist approach offers a promising alternative to the traditional efficient market hypothesis. Asset price movements may be amplified by nonlinear trading rules or due to a switching between linear predictors. For instance, Day and Huang (1990) derive complex dynamics from a nonlinear fundamental trading rule whereas in the models of Chiarella (1992) and Farmer and Joshi (2002) the agents apply nonlinear technical trading rules. The switching process developed by Kirman (1991) depends on social interactions. In Brock and Hommes (1998), the traders tend to select predictors which have been profitable in the recent past. Lux and Marchesi (2000) elegantly combine social interactions and profit considerations.

What is the contribution of this branch of research? On the one hand, these models are remarkably successful in replicating the stylized facts of financial markets. On the other hand, these models have clearly improved our knowledge about what is going on in the markets. A main insight is that asset prices are at least partially driven by an endogenous nonlinear law of motion. In the near future we may hopefully be able to study the consequences of regulatory means, such as price limits, within computer-based laboratory markets to improve market efficiency (Westerhoff 2002).

The above models focus on one risky market only. Our paper suggests a framework in which traders are allowed to switch between a number of different speculative markets. The working of the model is roughly as follows. Fundamentalists are regarded as experts who specialize in one market and thus stay in that market. In contrast, chartists use rather flexible extrapolative methods to forecast prices. Chartists are thus not restricted to a certain market. Note that if the composition between chartists and fundamentalists varies, the stability of the markets may be affected. For instance, if the market impact of chartists exceeds a critical threshold, prices may be driven away from fundamentals.

The aim of this paper is to improve our understanding of multi-asset market dynamics. We also explore the extent to which our model is able to mimic the stylized facts of financial markets. As it turns out, our model produces almost unpredictable prices, lasting bubbles, excess volatility, fat tails for returns and volatility clustering. Since we focus on more than one risky asset, our approach allows us to study the relationship between different asset prices. For instance, we are able to confirm Shiller´s (2000) hypothesis that comovements in stock prices may occur if the agents´ perception of the fundamental value of a stock is anchored to the price evolution of other stocks.

The paper is organized as follows. In section 2, we review the empirical foundations of the chartist-fundamentalist approach. Section 3 presents the model, its calibration and a steady-state solution. In section 4, we explore the dynamic properties of the model. The last section concludes the paper.

2 Motivation

Chartist-fundamentalist models are motivated by solid empirical regularities. Let us briefly sketch some of the most crucial findings. Experimental evidence (e.g. Kahneman, Slovic and Tversky 1986, Smith 1991, Simon 1997) reveals that agents are not fully rational. Agents typically lack the cognitive capabilities to derive fully optimal actions. However, this does not imply that they are irrational. Clearly, agents strive to do the right thing. Their behavior may best be described as a rule-governed behavior, meaning that they follow simple rules which have proven to be useful in the past. Since the rules experience a permanent natural selection pressure, the number of applied rules is quite limited.

Two related strands of literature are important for our line of research. Survey studies such as Taylor and Allen (1992) or Lui and Mole (1998) indicate that professional traders strongly rely on technical and fundamental analysis to predict future prices. Technical analysis aims at identifying trading signals out of past price movements. For instance, if prices increase, a buying signal is triggered. Fundamental analysis presumes that prices converge towards fundamental values. For instance, if prices are above fundamental values, selling is suggested. The work of Ito (1990) and Takagi (1991) point in a similar direction. Agents build either adaptive or regressive expectations.

Behind this evidence, let us further elaborate the idea of our model. Remember that fundamental analysis requires intensive research. Fundamentalists thus concentrate on a limited number of markets. For the sake of convenience, we assume that they focus on one market only. Technical analysis applies to all markets. Chartists are therefore much more flexible and may wander between markets. How do they do this? Chartists tend to enter markets which promise persistent price trends. Such a mechanism may generate interesting dynamics. For instance, if a market displays a high fitness for the chartists, it attracts an increasing number of chartists. Since chartists typically destabilize the market a bubble is likely to occur. However, every chartist knows that all bubbles eventually burst. If they react to this risk in the sense that they leave the market, fundamentalists may drive prices to more moderate values.

3 The Model

3.1 Setup

We consider k=1, 2, ... K asset markets of equal size. The evolution of the fundamental prices of the K assets depends on the news arrival process. The Log of the fundamental value of asset k in period t+1 evolves as

$$F_{t+1}^{k} = F_{t}^{k} + N^{k} . \tag{1}$$

News N^{k} is constant, equal among markets and arrives every trading period. Nevertheless, the true fundamental values are unknown to all market participants.

The prices of the *k* assets are determined on an order-driven market. The efficiency of the price discovery process depends on the behavior of the agents. Our focus is on three different types of agents: market makers, fundamentalists and chartists. All orders are initiated against market makers who stand ready to absorb imbalances between buyers and sellers. Depending on the excess demand, market makers adjust prices according to (Kyle 1985, Farmer 1998):

$$S_{t+1}^{k} = S_{t}^{k} + a^{M,k}(D_{t}^{F,k} + W_{t}^{k} D_{t}^{C,k}), \tag{2}$$

where S^{k} is the Log of the asset price in market *k*, $a^{M,k}$ is the reaction coefficient of the market makers in market *k*, $D^{F,k}$ and $D^{C,k}$ are the orders of fundamentalists and chartists respectively in market *k*, and W^{k} is the fraction of chartists who are currently active in market *k*. Note that excess buying drives prices up and excess selling drives them down.

Since all markets are equal in size, a price index is given as

$$I_{t+1} = Log[\frac{1}{K}\sum_{k=1}^{K} Exp[S_{t+1}^{k}]]. \tag{3}$$

The Log price index *I* is the average of Log prices of the *k* markets.

The traders submit buying (selling) orders if they expect an increase (decrease) in the price. The demand of the speculators is expressed as

$$D_{t}^{F} = a^{F,k}(E_{t}^{F}[S_{t+1}^{k}] - S_{t}^{k}), \tag{4}$$

and

$$D_{t}^{C} = a^{C,k}(E_{t}^{C}[S_{t+1}^{k}] - S_{t}^{k}), \tag{5}$$

where $a^{F,k}$ and $a^{C,k}$ denote the reaction coefficients of fundamentalists and chartists, respectively. Such demand functions are in harmony with myopic mean-variance maximizers (Hommes 2001).

Fundamentalists expect the prices of the assets to return towards their fundamental values. Such regressive expectations may be expressed as

$$E_t^F[S_{t+1}^k] = S_t^k + b^{F,k}(P_t^k - S_t^k), \tag{6}$$

where $b^{F,k}$ stands for the expected adjustment speed of the Log asset price towards its perceived Log fundamental value P^k. Chartists display bandwagon expectations

$$E_t^C[S_{t+1}^k] = S_t^k + b^{C,k}(S_t^k - S_{t-1}^k). \tag{7}$$

The degree of extrapolation is given by $b^{C,k}$. Similar expectation formation processes are, for instance, used by Kirman (1991).

Remember that the true fundamental values are unknown. Nevertheless, traders frequently talk about fundamentals. Some of them even place orders on what they perceive as fundamental values. Experimental evidence suggests that agents perceive fundamental values according to the anchor and adjustment heuristic. Tversky and Kahneman (1974) report that people make estimates by starting from an initial value that is adjusted to yield the final answer. However, adjustments are typically insufficient, implying biased estimates towards initial values. Here, the perception of the fundamental value is modeled as follows (Westerhoff 2001)

$$\begin{aligned} P_t^k &= Log[c^{1,k} Exp[P_{t-1}^k] + c^{2,k} Exp[I_{t-1}] + c^{3,k} Exp[S_{t-1}^k]] \\ &\quad + N^k + d^k (P_{t-1}^k - P_{t-2}^k - N^k) \\ &\quad + e^k (F_{t-1}^k - P_{t-1}^k) \quad . \end{aligned} \tag{8}$$

The first three elements of the right-hand side of (8) represent the anchor. The initial value for computing the fundamental value is a weighted average of P^k, I^k and S^k. The weights $c^{1,k}$, $c^{2,k}$ and $c^{3,k}$ are positive and add up to 1. The motivation for the formulation of the anchor is that many traders believe that asset prices themselves reflect relevant information (Murphy 1999).

The adjustment of the anchor takes place in two steps: First, traders naturally react to the arrival of new information. However, since the exact meaning of news is unknown, the agents tend to misperceive news. For instance, if the recent update of the perceived fundamental value has been above the news impact $(P_{t-1}^k - P_{t-2}^k > N^k)$, traders become optimistic and overreact to news. The degree of misperception is given by d^k. The second adjustment process covers the learning or research behavior of the agents. Psychologists argue that such error correction learning is typically slow over time and small in magnitude. Hence, e^k is positive but relatively small.

While fundamentalists stick to their markets, chartists regularly switch between them. According to Murphy (1999), the main principle of technical analysis is to ride on a bubble. But as is well known, eventually every bubble bursts. Clearly, there is a risk connected with such behavior. Chartists therefore try to identify the attractiveness of a market as

$$A_t^k = Log \frac{1}{1 + f^k (P_t^k - S_t^k)^2}. \qquad (9)$$

The bell-shaped form of the above fitness measure is bounded between -∞ and 0 and entails the risk of being caught in a bursting bubble. For $P^k = S^k$, the attractiveness of a market reaches its maximum value 0. The larger the distance between P^k and S^k, the lower the fitness of the market $(f^k > 0)$.

The probability that a chartist enters market *k* is given by the discrete choice model of Manski and McFadden (1981)

$$W_t^k = \frac{Exp(g^k A_t^k)}{\sum_{k=1}^{K} Exp(g^k A_t^k)}. \qquad (10)$$

The higher the attractiveness of market *k*, the more chartists will enter that market. The parameter g^k is called the intensity of choice and measures how sensitive the mass of traders is to selecting the most attractive market. Note that an increase in the intensity of choice may be interpreted as an increase in the rationality of the traders. For $g^k = 0$, the chartists do not observe any differences in the fitness of the markets. As a result, they are even divided into markets. If g^k goes to infinity, all chartists enter the market with the highest fitness. The use of a discrete choice model in the context of heterogeneous agents´ economies has been popularized by Brock and Hommes (1997).

The solution of the model, obtained by combining (1) to (10), is a high-dimensional nonlinear difference equation system. Since the law of motion of the asset prices precludes closed analysis we proceed with a numerical analysis.

3.2 Calibration

Table 1 displays the parameter setting we use for the simulation analysis. Unfortunately, empirical guidance on how to pick the parameters of chartist-fundamentalist models is limited. Let us briefly attempt to interpret our choice. We consider 5 symmetric asset markets (i.e. the coefficients are equal across markets). Since we calibrate the model to daily data, the news level corresponds to a trend growth of 5 percent per year. The total market impact of chartists is somewhat higher than that of fundamentalists. But note that chartists split up into 5 markets. The price index enters the anchor with 0.5 percent and the asset price with 1.5 percent. The misperception of news coefficient is close to 1. The adjustment due to learning is rather small.

Table 1 goes about here

Overall, it should be fairly simple to replicate our results. Simulations indicate that we are not dealing with a special case, i.e. the dynamic behavior is robust for a broad range of parameters. Bifurcation diagrams surprisingly do not reveal the usual routes to chaos such as period-doubling bifurcation. Instead, one mainly finds regions with stable, chaotic or unstable orbits. We skip such technical considerations and concentrate on the economic reasons behind the dynamics.

3.3 A Steady-State Solution

Let us begin our analysis by looking at a special case. Suppose the following initial values: $F_0^k = S_0^k = P_0^k$ and $F_1^k = S_1^k = P_1^k$ for all *k*. Then the solution of the model is a steady state. Note first that the agents perceive the fundamental value correctly. Therefore, the demand of the fundamentalists is zero. Ironically, it is the behavior of the chartists that ensures efficiency. Their trading rules pick up the trend growth correctly. Since chartists are divided evenly across the markets, all asset prices increase at the rate of the news level.

As long as the shocks are equal across the markets in period 1, the attractiveness of the markets does not differ. Since $W_t^k = 1/K$, our model basically collapses into a linear model. In order to make use of the multi-asset market framework, the initial values for the asset prices in period 1 are thus set slightly differently.

4 Simulation Analysis

4.1 Symmetric Markets

Figure 1 displays the dynamics for 400 observations starting in period 650. The top panel shows the Log of the price index, the second panel shows the Log of the asset price of market *k*=2, and the third panel shows the fraction of chartists which are active in market *k*=2. Visual inspection reveals that asset prices fluctuate in an intricate fashion.[1] The dynamics of the

[1] The dynamic behavior we discuss in section 4 is independent of the assumed trend growth in the fundamental value. However, since asset markets show an exponential increase in the long run, we have included a drift term. In addition, it is sometimes conjectured that chartist-fundamentalist models have difficulties to mimic the stylized fact of financial markets in a non-stationary setting. This is – at least – not the case for our model.

aggregate market seems to be even more complex than the dynamics of the individual markets. For instance, small price swings alternate with large price swings. The degree of fluctuations appears to be lower in the index market. Finally, the chartists wander quickly between markets.

Figure 1 goes about here

What drives the dynamics? Broadly speaking, chartists tend to destabilize the markets whereas fundamentalists exercise a stabilizing impact on the dynamics. If there are more fundamentalists than chartists in a market, prices are pushed towards (perceived) fundamentals. However, such a development increases the attractiveness of the market for the chartists. As a result, more and more chartists enter the market, which in turn drives prices away from equilibrium values. This development decreases the attractiveness of the market until the fundamentalists are in the majority again.

Figure 2 presents the dynamics for the first 10,000 observations. The top panel shows the price index and the central panel the price of market k=2. The smooth lines in the top two panels indicate the evolution of the fundamental value. Obviously, the model is able to generate bubbles. Prices may deviate strongly and persistently from fundamental values. Further simulations reveal that bubbles occur in both directions. Due to the trend growth, technical analysis generates more overshooting than undershooting: Prices are 53 percent of the time above fundamental values (average value over 50 simulation runs, each containing 10,000 observations).

Figure 2 goes about here

The bottom panel displays the distance between the highest and the lowest price of the 5 markets. Sometimes, the markets move closely together. However, differences between the prices may become as large as 40 percent. Shiller (1989) reports that stock prices move strongly together. More precisely, comovements in stock prices are much larger than comovements in fundamentals. For example, after the stock market crash in 1987, the levels of stock prices in all major stock markets around the world made similarly spectacular drops. Shiller (2000) argues that for individual stocks, price changes tend to be anchored to price changes of other stocks via the expectation formation and perception process.

Our model allows the investigation of this hypothesis. Table 2 shows how dispersion and distortion are influenced by the perception of fundamental values. Dispersion is defined as the average distance between the highest and the lowest price of the K markets

$$dispersion = \frac{1}{T}\sum_{t=1}^{T} \max_k [S_t^k] - \min_k [S_t^k]\,. \tag{11}$$

Distortion is computed as the average absolute distance between the price index and the fundamental value

$$distortion = \frac{1}{T}\sum_{t=1}^{T} | I_t - F_t |\,. \tag{12}$$

All estimates are averages over 50 simulation runs, each containing T=10,000 observations. The gray shaded numbers indicate the outcome for the parameter setting of table 1. On average, we observe a dispersion of 6.4 percent and a distortion of 9.4 percent.

Table 2 goes about here

If the traders rely more strongly on the price index as an anchor, then the distortion increases but the dispersion decreases. On the one hand, mistakes in the pricing of the assets are transferred into a misperception of the fundamentals. Therefore, bubbles become more pronounced. On the other hand, by using the price index more strongly as an anchor, the agents perceive rather similar fundamental values across markets. Since perceived fundamentals attract prices, comovements in prices increase. Hence, our analysis supports Shillers´ hypothesis.

The picture for the market price as an anchor appears differently. The higher the c^3, the higher the dispersion and distortion. For instance, for $c^3 = 0.05$, dispersion is 7.5 percent and distortion is 14 percent. Again, a mispricing of the assets is transformed into a misperception of fundamental values. But now the individual markets show a life on their own. If the misperception of news coefficient approaches 0.99, distortion and dispersion increase sharply. For $d > 0.99$, the dynamics are likely to explode. Learning decreases the level of mispricing but surprisingly has almost no impact on the degree of the comovements of stock prices.

Figure 3 displays the evolution of the returns in the time domain for 10,000 periods. The top 5 panels show the return time series for the 5 asset markets, whereas the bottom panel shows the return time series for the index market. Single returns in individual markets may be larger than 20 percent. Extreme price changes of the aggregated market are around 7 percent. Since the trend growth of the markets is 5 percent per year, volatility is quite excessive. Moreover, there is clear evidence of volatility clustering (Mandelbrot 1963). Periods of high volatility are also correlated across markets.

Figure 3 goes about here

Extreme price changes occur as follows. Remember that market makers adjust prices strongly when they have to mediate a high excess demand. This may be the case when a market with a high concentration of chartists displays a strong technical trading signal. The order size may even be higher if fundamentalists trade in the same direction. Note that an extreme price change may indicate the next clear trading signal for the chartists. Therefore, volatility may remain elevated for some time.

But there is also another, possibly more important, origin of a volatility outburst. The bottom part of figure 1 indicates that chartists switch rather quickly between markets. However, this may not always be the case. If all markets are simultaneously in a bubble process, then chartists have no reason to leave the market. Clearly, chartists may stick to a market which is highly volatile and distorted. Further simulations reveal that the degree of volatility clustering decreases with an increase in the intensity of choice coefficient.

Figure 4 contains estimates of the tail index for the 5 asset markets and the index market. The tail indices are computed with the Hill tail index estimator (Hill 1975) using 0 to 6 percent of the largest observations. The results are shown for 20 simulation runs, each containing 10,000 observations. Actual financial data is characterized by tail indices between 2 and 5 (Farmer 1999, Lux and Ausloos 2000). The tail indices of the 5 artificial markets hover between 2.5 and 3.5 at the 5 percent level. Most estimates of the aggregated market scatter between 3 and 5. Hence, our results are in harmony with estimates obtained for real financial markets.

Figure 4 goes about here

So far we have demonstrated that the model produces bubbles, excess volatility, fat tails for returns and volatility clustering. Finally, we explore the extend to which the generated time series are unpredictable. Figure 5 shows the dynamics in phase space. The top left panel shows $S^1_{t+1} - P^1_{t+1}$ versus $S^1_t - P^1_t$, the top right panel shows $S^3_{t+1} - S^3_t$ versus $S^1_{t+1} - S^1_t$, the bottom left panel shows $S^1_{t+1} - S^1_t$ versus $S^1_t - S^1_{t-1}$, and the bottom right panel shows $I_{t+1} - I_t$ versus $I_t - I_{t-1}$. A lot of structure is visible. For instance, in the bottom left panel one would expect a scatter plot with no visible patterns. However, a so-called strange attractor emerges. At least the figure in the bottom right panel resembles a cloud with almost no structure.

Figure 5 goes about here

The correlation dimension is a measure to determine the degree of complexity of such objects. Figure 6 shows estimates of the correlation dimension with respect to increasing embedding dimensions. The "Chaos Data Analyzer" software developed by Sprott and Rowlands (1995) allows us to calculate the correlation dimension for embedding dimensions up to 10. A proper estimate for the correlation dimension is obtained if the estimates converge to some almost constant value. This is, for instance, the case for the return time series of market 1 (the line with the circles). The correlation dimension is about 3.1.

Figure 6 goes about here

A truly stochastic process exhibits increasing estimates of the correlation dimension with increasing embedding dimensions. The top line shows the estimates for normally distributed returns. Clearly, the correlation dimension does not converge to a constant value. The line with the black squares shows estimates for daily Dow Jones returns between 1974 and 1998. Although this line does not converge to some constant value either, it seems that the dynamics are slightly less complex than the random walk process (see Chen, Lux and Marchesi 2001). The line with the black circles visualizes the case for the returns of the index market. At least for embedding dimensions up to 10, there is no convergence. The estimates are slightly below the estimates for the Dow Jones data. However, a correlation dimension of above 6 indicates highly complex dynamics.

4.2 Asymmetric Markets

So far we have dealt with symmetric markets. The coefficients of the model have been assumed to be equal across markets. Finally, we briefly explore what happens if the markets are asymmetric. It shows that for most coefficients the typical patterns of the dynamics is robust. However, the complexity of the dynamics may further increase.

Figure 7 contains autocorrelation functions for raw returns and absolute returns. The left- hand panels show the estimates for the symmetric markets. We find a typical autocorrelation function for absolute returns, but the autocorrelation for raw returns is much too high. Indeed, financial data displays only weak autocorrelation in raw returns (Campbell et al. 1997, Mantegna and Stanley 2000). The right-hand panels present the estimates for the asymmetric markets (i.e. the coefficients $a^{F,k} b^{F.k}$ vary between 0.1 and 0.3 across markets). Although the impact on the autocorrelation of absolute returns is modest, the mean reversion tendency is much lower. Introducing even more asymmetries decreases the autocorrelation of raw returns further.

Figure 7 goes about here
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5 Conclusion

Chartist-fundamentalist models have proven to be quite successful in explaining the stylized facts of financial markets. Contributions such as Day and Huang (1990), Kirman (1991), Chiarella (1992), Brock and Hommes (1998), Lux and Marchesi (2000) and Farmer and Joshi (2002) focus, however, on one risky market only. This paper develops a framework in which traders are allowed to switch between markets. Since fundamental analysis requires intensive observation of the market, fundamentalists concentrate on one market only. The use of extrapolative methods allows chartists to switch between markets. Chartists tend to enter those markets which show price trends but which are not too misaligned. The interaction between the traders causes complex dynamics. Prices are highly unpredictable, excessively volatile and may deviate from fundamentals. In addition, the prices of the assets move closely together. The reason is that if agents anchor their perception of fundamental values to the evolution of the price index, they perceive rather similar fundamental values across markets. Our model also produces fat tails for returns and volatility clustering.

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K=5	N=0.0002	a^M=1	$a^C b^C$=5	$a^F b^F$=0.2	c^1=0.98
c^2=0.005	c^3=0.015	d=0.99	e=0.00005	f=1,000,000	g=1.2

Table 1: Parameter Setting. All markets are symmetric. Initial values for *S*, *P* and *F* are 0.

index anchor c^2	0.010	0.020	0.030	0.040	0.050
dispersion	0.056	0.050	0.044	0.040	0.036
distortion	0.099	0.125	0.114	0.124	0.121

market anchor c^3	0.010	0.020	0.030	0.040	0.050
dispersion	0.061	0.065	0.069	0.073	0.075
distortion	0.082	0.090	0.114	0.116	0.140

misperception of news d	0.190	0.390	0.560	0.790	0.990
dispersion	0.028	0.025	0.024	0.027	0.064
distortion	0.021	0.027	0.034	0.040	0.094

learning e	0.0001	0.0002	0.0003	0.0004	0.0005
dispersion	0.063	0.062	0.063	0.062	0.062
distortion	0.057	0.040	0.034	0.028	0.025

Table 2: The Impact of the Perception Process on Dispersion and Distortion. Parameter setting as in table 1 or as indicated above. Estimates are averages over 50 simulation runs, each containing 10,000 observations. The gray shaded numbers indicate the outcome for the parameter setting of table 1.

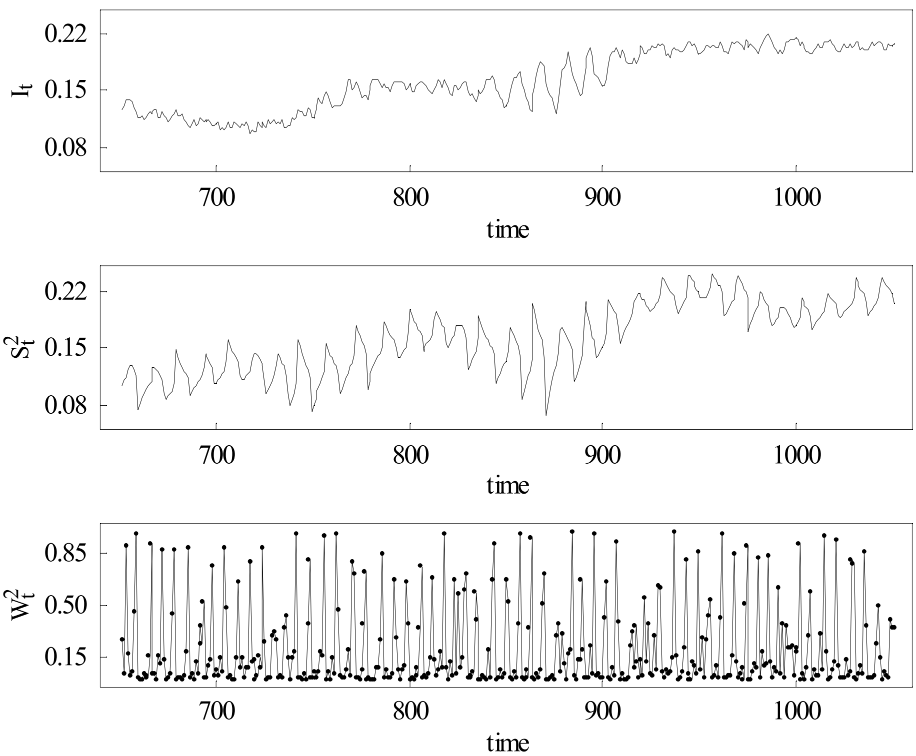

Figure 1: The Dynamics in the Short Run. The first panel shows the Log of the price index, the second panel shows the Log of the price of market 2 and the third panel shows the fraction of chartists which are active in market 2. The dynamics are plotted for 400 periods, starting in t=650. Parameter setting as in table 1.

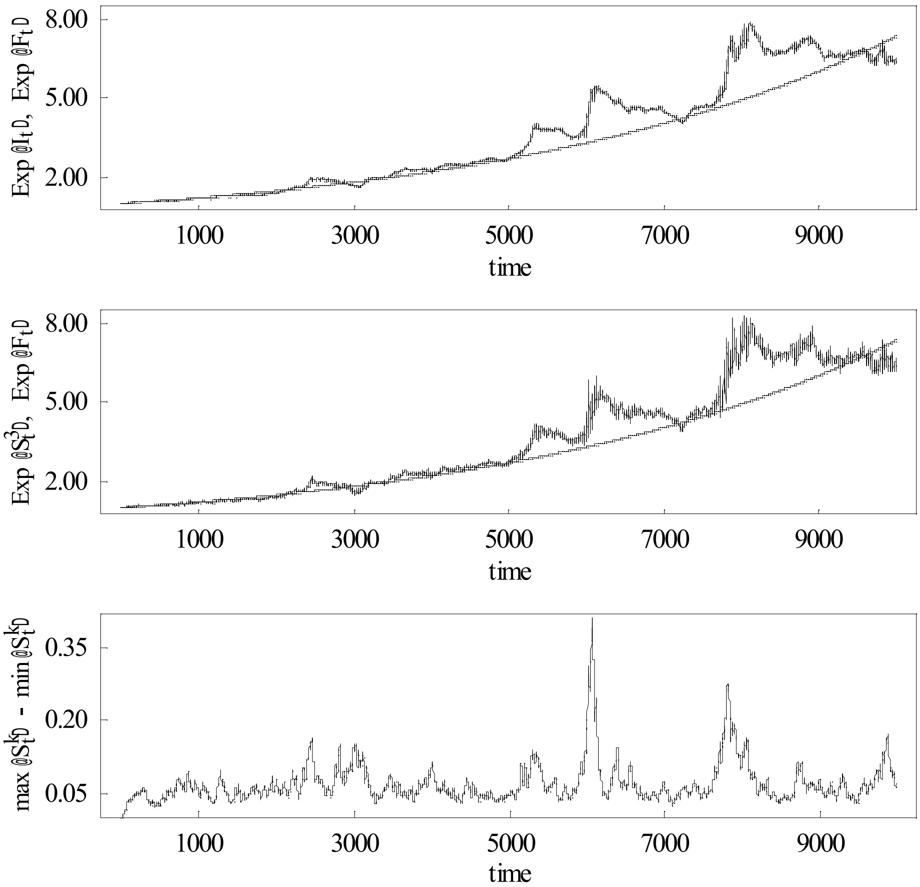

Figure 2: The Dynamics in the Long Run. The first panel shows the price index and its fundamental value (the smooth line), the second panel shows the price of market 3 and its fundamental value (the smooth line) and the bottom panel shows the deviation between the Log of the largest price and the Log of the smallest price of the 5 markets. The dynamics are displayed for 10,000 observations. Parameter setting as in table 1.

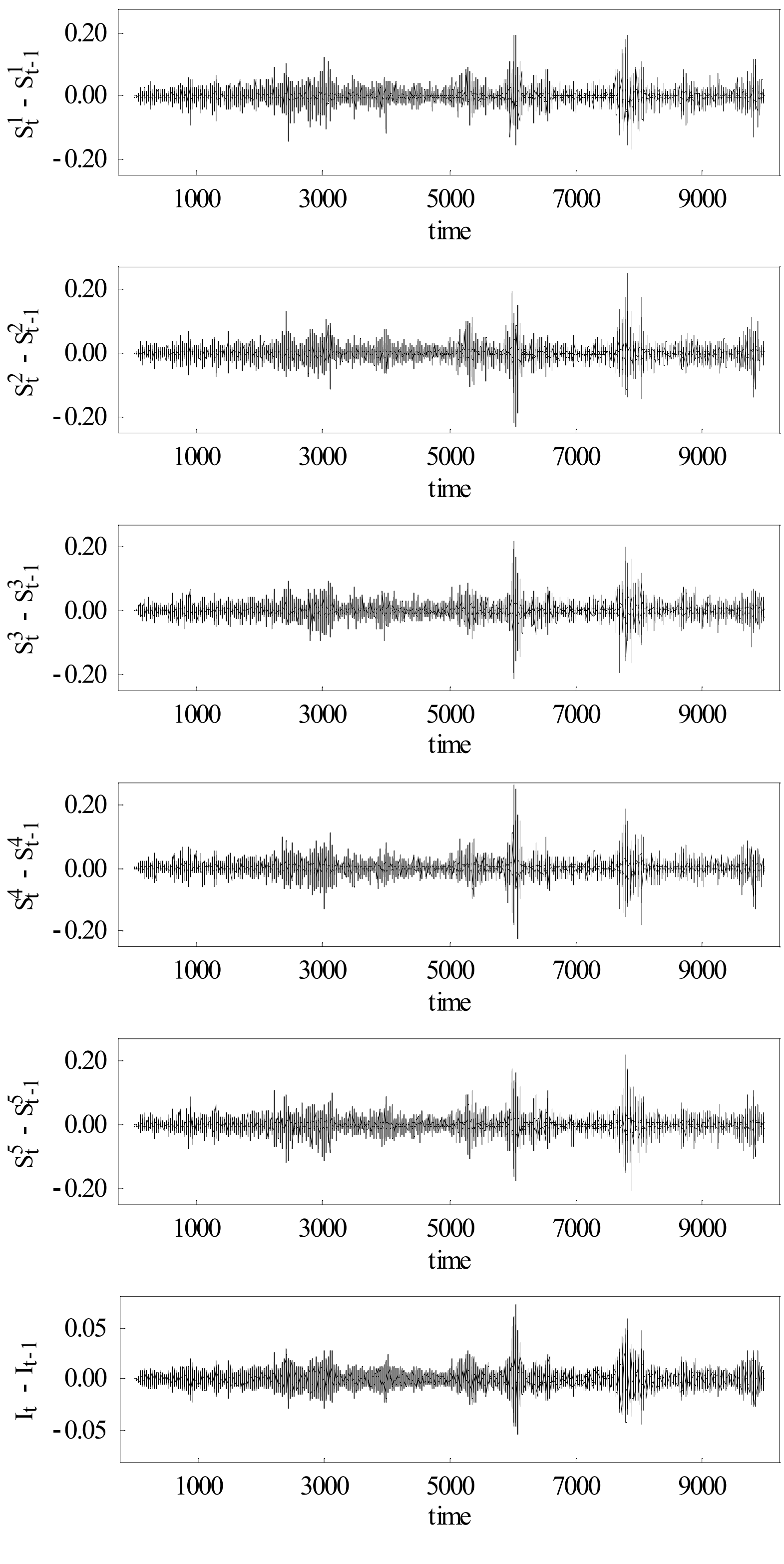

Figure 3: The Evolution of the Returns. The first 5 panels show the returns of the 5 asset markets and the bottom panel shows the returns for the index market. The dynamics are displayed for 10,000 observations. Parameter setting as in table 1.

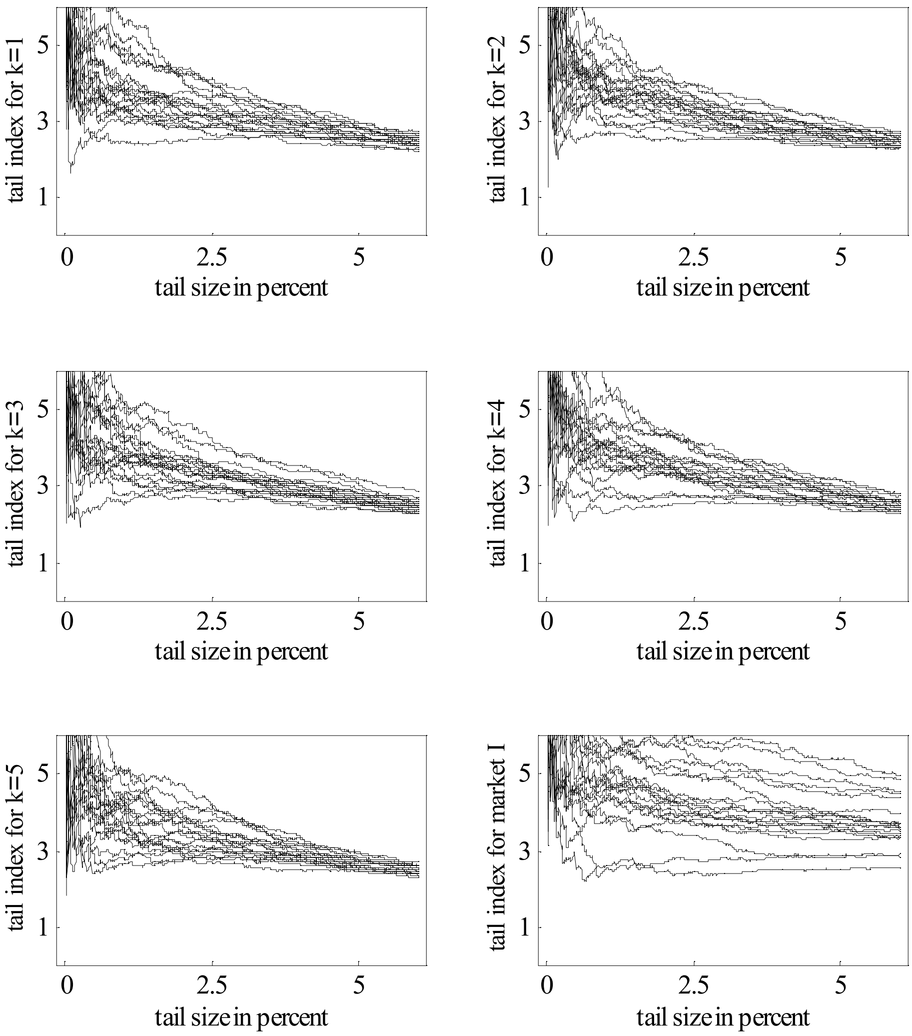

Figure 4: Estimation of the Tail Index. The 6 panels show the tail indices for the 5 asset markets and the index market for increasing tail sizes (0 to 6 percent of the largest observations). Every panel contains the estimates for 20 simulation runs, each containing 10,000 observations. Parameter setting as in table 1.

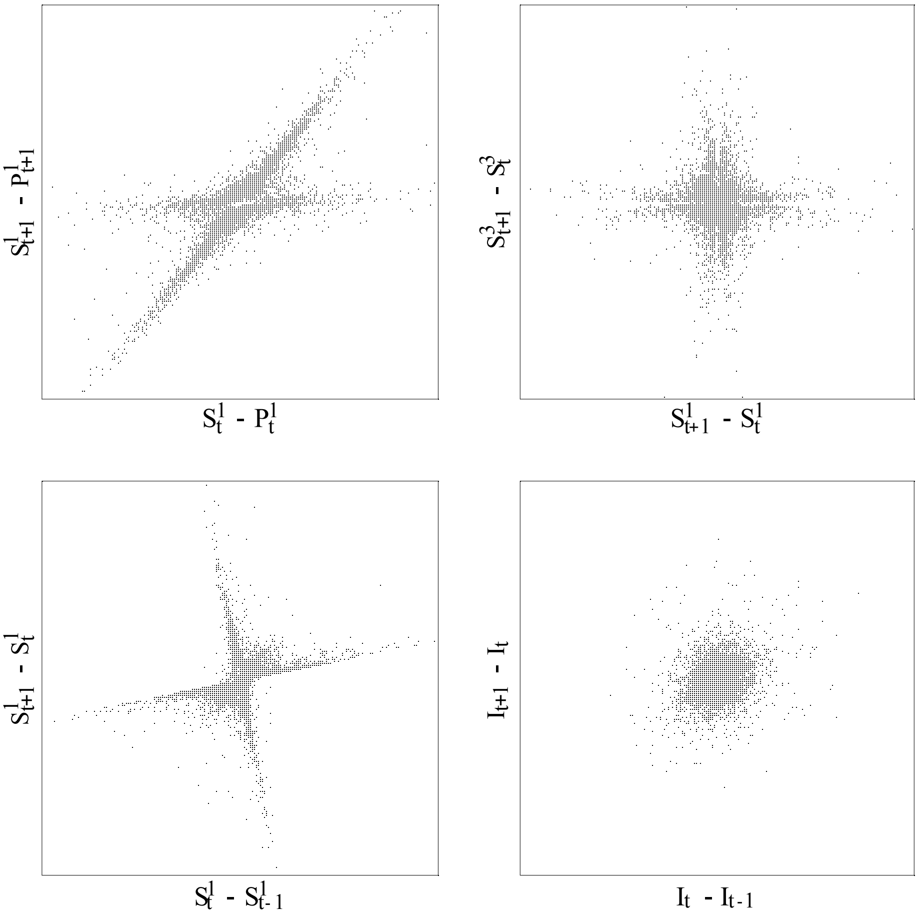

Figure 5: The Dynamics in Phase Space. The top left panel shows an attractor for deviations between the price and the perceived fundamental value of market 1 in period t+1 versus period t, the top right panel shows an attractor for price changes of market 3 versus price changes of market 1, the bottom left panel shows an attractor for price changes of market 1 in period t+1 versus price changes in period t and the bottom right panel shows the same for the index market. The dynamics are displayed for 10,000 observations. Parameter setting as in table 1.

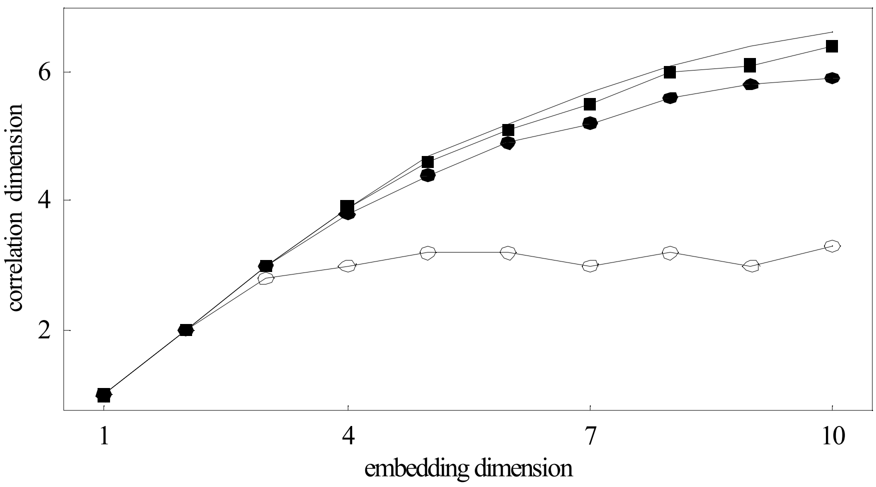

Figure 6: Estimation of the Correlation Dimension. The first line from the top shows the estimates for normally distributed returns, the second line from the top shows the estimates for daily Dow Jones returns between 1974 and 1998, the third line from the top shows the estimates for the returns of the index market and the bottom line shows the estimates for the returns of market 1. All artificial return time series contain 10,000 observations. Parameter setting as in table 1.

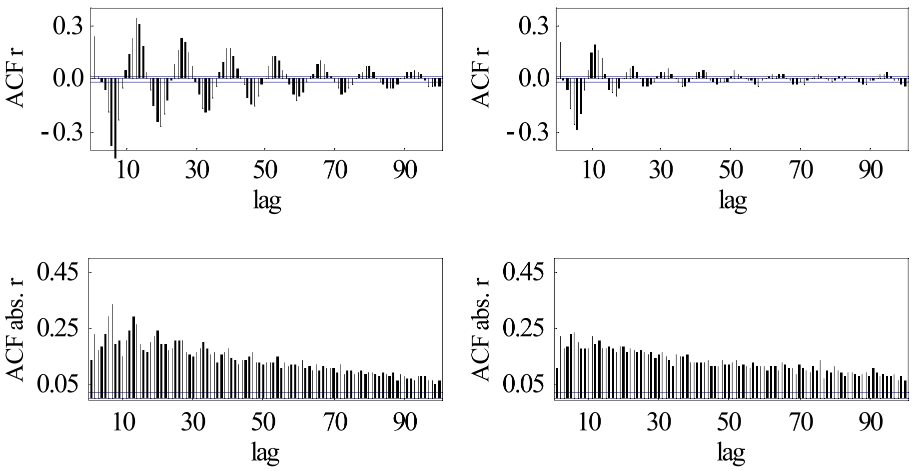

Figure 7: Asymmetric Markets and Predictability. The top left (bottom left) panel shows the autocorrelation function for raw (absolute) returns of the index market (T=10,000 observations). Parameter setting as in table 1. The right-hand side shows the same but $a^F b^F$ varies between 0.1 and 0.3 across the 5 asset markets. Ninety-five percent confidence intervals are plotted as $\pm 2/\sqrt{T}$ (assumption of white noise).