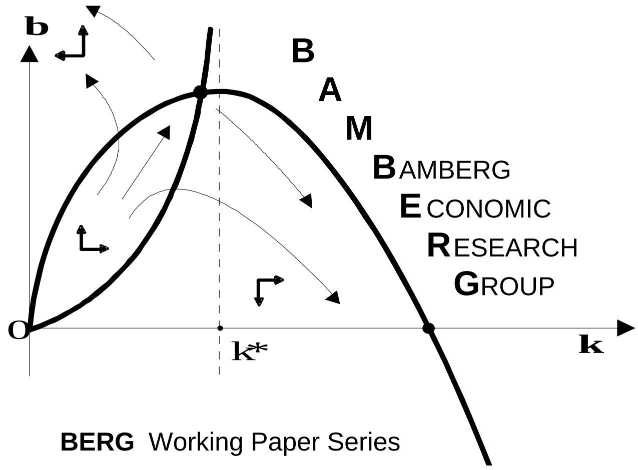
Speculative behavior and the dynamics of interacting stock markets

Noemi Schmitt and Frank Westerhoff

Working Paper No. 90

November 2013



Bamberg Economic Research Group
Bamberg University
Feldkirchenstraße 21
D-96052 Bamberg
Telefax: (0951) 863 5547
Telephone: (0951) 863 2687
felix.stuebben@uni-bamberg.de
http://www.uni-bamberg.de/vwl/forschung/berg/

ISBN 978-3-943153-05-7

Speculative behavior and the dynamics of interacting stock markets *

Noemi Schmitt and Frank Westerhoff **

University of Bamberg, Department of Economics

Abstract

We develop a simple agent-based financial market model in which heterogeneous speculators apply technical and fundamental analysis to trade in two different stock markets. Speculators' strategy/market selections are repeated at each time step and depend on predisposition effects, herding behavior and market circumstances. Simulations reveal that our model is able to explain a number of nontrivial statistical properties of and between international stock markets, including bubbles and crashes, fat-tailed return distributions, volatility clustering, persistent trading volume, coevolving stock prices and cross-correlated volatilities. Against this background, our model may be deemed to have been validated.

Keywords

Stock markets; stylized facts; technical and fundamental analysis;

agent-based modeling; bounded rationality; simulation analysis.

JEL classification

C63; D84; G12.

---

* Presented at the "CeNDEF@15 Symposium", Amsterdam, October 2013, "The 1st GENED Meeting", Bielefeld, September, 2013, "The 8th International Conference on Nonlinear Economic Dynamics", Siena, July 2013, and at the "International Workshop on Nonlinear Dynamics, Agent-based Models, and Complex Evolving Systems in Economics", Bologna, June 2013. We thank the participants for their stimulating feedback.

** Contact: Frank Westerhoff, University of Bamberg, Department of Economics, Feldkirchenstrasse 21, D-96045 Bamberg, Germany. Email: frank.westerhoff@uni-bamberg.de.

1 Introduction

Agent-based financial market models have undoubtedly improved our understanding of how financial markets function. For reviews of this burgeoning field of research see, for instance, Chiarella et al. (2009), Hommes and Wagener (2009) or Lux (2009). Within these models, market participants rely on technical and fundamental analysis for their trading purposes. Technical analysis is a trading strategy which aims at exploiting price trends. In contrast, fundamental analysis seeks to profit from mean reversion. These model ingredients are crucial, yet not based on ad-hoc assumptions. Questionnaire studies, summarized by Menkhoff and Taylor (2007), unanimously confirm that professional market participants indeed use technical and fundamental analysis. A similar observation is made in laboratory experiments. As reported by Hommes (2011), human subjects use relatively simple extrapolative and regressive forecasting rules to predict financial markets. Without going into details, we merely note that deterministic agent-based financial market models (e.g. Day and Huang 1990, de Grauwe et al. 1993, Lux 1995, Brock and Hommes 1998, Chiarella et al. 2002, Huang et al. 2010, Tramontana et al. 2010) are able to produce intricate boom-bust cycles while stochastic model versions (e.g. Lux and Marchesi 1999, Farmer and Joshi 2002, Westerhoff 2003, Gaunersdorfer and Hommes 2007, He and Li 2007, Franke 2010) may match the statistical properties of financial markets in detail. Due to their apparent power, agent-based financial market models are increasingly used as tools for economic policy design (see Westerhoff and Franke 2013 for a survey).

Unfortunately, research into this area has neglected – with very few exceptions – to study interactions between international financial markets. This is particularly troublesome since past experience repeatedly shows that global financial crises involving the collapse of major stock markets around the world pose a severe threat to the stability of the whole economic system. To unravel possible mechanisms for the strong synchronized behavior of international stock markets, both with respect to their price levels (e.g. Shiller 1989) and to their volatilities (e.g. Edwards and Susmel 2001), we develop an agent-based financial market model in which speculators have the opportunity to trade in two different stock markets. Our model is structured as follows. Speculators determine their orders based on technical and fundamental analysis. In this respect, three modeling aspects are important. First, technical analysis is based on trend extrapolation, and fundamental analysis is based on mean reversion. Second, to capture part of the variety of actual technical and fundamental trading rules, speculators' trading behavior contains a random component. Third, since speculators are also influenced by a number of common factors – namely business gossip, political rumors, or waves of optimism and pessimism – their trading behavior is not independent. Another important feature of our model is that speculators can switch between trading strategies and markets. The speculators' selection of strategy/market combinations is repeated every trading period and influenced by predisposition effects, herding behavior and market circumstances. Finally, market makers mediate all transactions and adjust prices with respect to excess demands in the usual way.

Simulations reveal that our model is able to explain a number of important stylized facts of stock markets, e.g. bubbles and crashes, excess volatility, fat-tailed return distributions, uncorrelated returns, volatility clustering, temporal dependence of trading volume and positive relations between volatility and trading volume. Compared to the aforementioned literature, however, our model is furthermore able to replicate a number of key dynamic relationships between international stock markets. In particular, speculators' trading behavior may cause comovements of stock prices, cross-correlations of volatilities and positive relationships between stock markets' trading volumes. Since our approach is capable of replicating a diverse set of stylized facts, it may be deemed to have been validated.

In a nutshell, the model dynamics evolves as follows. Speculators relying on technical analysis tend to destabilize markets, while speculators using fundamental analysis stabilize them. Suppose that prices are close to fundamentals. Most speculators then prefer technical trading, and stock markets experience stronger price fluctuations. However, the more stock prices deviate from fundamentals, the more speculators turn their attention towards fundamental analysis. If a sufficient number of speculators uses fundamental analysis, stock markets start to calm down and we observe fundamental price corrections and lower volatilities. But how do stock market interactions come about? Since speculators' orders are influenced by common factors, excess demands and, consequently, stock price changes are correlated across markets. Coevolving stock prices imply, in turn, that speculators perceive the attractiveness of technical and fundamental analysis across markets as being relatively similar. As a result, the relative proportions of technical and fundamental analysis do not differ much across markets, which strengthens the coevolution of stock prices and creates cross-correlation in volatilities. Of course, speculators may temporarily herd to one particular stock market. Their aggregate forces can then induce extreme price changes, dramatic bubbles or severe crashes.

Our model may be regarded as an extension of that by Franke and Westerhoff (2012). While they concentrate on the dynamics of a single stock market, we go one step further and study interactions between two stock markets. Agent-based models focusing on multiple markets are, unfortunately, rare. The papers linked most closely to ours are outlined below. Westerhoff (2004) considers a multi-asset market model with chartists and fundamentalists. Chartists exit and enter markets, creating alternating periods of stability and instability. His deterministic model produces chaotic price dynamics, but is unable to match the stylized facts of stock markets in greater detail. Huang and Chen (2013) also develop a deterministic chartist-fundamentalist model with two interacting stock markets. Their setup allows the propagation of financial crisis from one market to the other to be studied. From a qualitative perspective, it is able to reproduce a number of dynamic features of actual stock markets. Westerhoff and Dieci (2006) develop a stochastic model in which speculators select between technical and fundamental trading rules and between two speculative markets. The switching dynamics is modeled via a discrete choice approach, as proposed by Brock and Hommes (1998), using past profits as the relevant fitness criterion. A related scenario is developed in Pape (2007). He models the switching dynamics via a transition probabilities approach, as in Lux (1995), and considers in this respect herding behavior and expected profit opportunities. While both models can mimic the dynamics of individual markets quite well, they fail to produce comovements of stock prices and cross-correlations of volatilities. Anufriev et al. (2012) propose a high-dimensional, stochastic multi-asset market model in which different investment strategies may coexist to explain the presence of excess covariance of stock market returns. Their approach is quite flexible; traders' choices of investment strategies may be affected by predisposition effects and the strategies' relative past performance.

In a series of papers, Chiarella et al. (2005) and Chiarella et al. (2007, 2009, 2013a) add boundedly rational speculators to standard mean-variance portfolio frameworks with multiple risky assets. They investigate whether speculators' dynamic portfolio decisions and beliefs about asset returns and their correlations stabilize or destabilize financial markets. The recent evolutionary CAPM presented in Chiarella et al. (2013b), in which speculators switch between technical and fundamental prediction rules with respect to their past performance, has a certain amount of ability to generate realistic stock price dynamics. Compared to their sophisticated and elegant models, we strive for a simpler behavioral approach, attempting to bring our setup closer to the data.

A few papers are also devoted to the interplay between stock and foreign exchange markets. To gain deeper insights into the stability of the global financial system, Dieci and

Westerhoff (2010) develop a deterministic model in which the stock markets of two countries are linked via and with the foreign exchange market. They find that nonlinear interactions between technical and fundamental traders in the foreign exchange market may create bull and bear market dynamics within the whole financial system. Corona et al. (2008) suggest a model with stock and foreign exchange markets in which speculators follow random, momentum, contrarian and fundamental strategies. Speculators stick to their trading rules but seek to switch to the most profitable market. Their model can be considered a 'large-scale model' because it keeps track of the activities of a larger number of individual traders. As in the simulations of Westerhoff and Dieci (2006) and Pape (2007), the dynamics of individual markets appear to be quite realistic, yet this does not hold for major relationships between them. Kirman et al. (2007) develop a two-country, agent-based financial market model in which the demand of speculators for foreign currency may create substantial bubbles in the foreign exchange market.

The model by Feldman (2010) also belongs to the class of large-scale agent-based models. Within his setup, speculators make investment decisions based on the mean-variance framework to invest in two stock markets (the exchange rate is fixed), but also suffer from behavioral biases with respect to their risk attitudes. Interestingly, a global financial crisis may emerge if the number of speculators is sufficiently high. Chen and Hung (2008) develop a computational multi-asset artificial stock market model to study how risk preferences and prediction accuracies affect the survival chances of heterogeneous speculators. Finally, we mention Brock et al. (2009) who show that more hedging instruments may, in the presence of heterogeneous speculators, be harmful to the stability of financial markets.

The remainder of this paper is organized as follows. In Section 2, we briefly recap a number of important stylized facts concerning stock markets, focusing on the behavior of individual stock markets and on key dynamic relationships between them. In Section 3, we introduce a simple agent-based financial market model in which speculators, who rely on technical and fundamental analysis, trade in two stock markets. In Section 4, we first study the dynamics of our model and show that its time series properties are quite similar to the time series properties of actual stock markets. Second, we endeavor to explain how our model functions. In Section 5, we summarize our main results and illustrate potential avenues for future work.

2 Some important stylized facts of stock markets

This section reviews a number of statistical properties of and between international stock markets, namely: (i) bubbles and crashes, (ii) excess volatility, (iii) fat-tailed return distributions, (iv) random-walk price behavior, (v) volatility clustering, (vi) comovements of prices, (vii) cross-correlations of volatilities, (viii) persistent trading volume, (ix) cross-correlations of trading volume and volatility and (x) cross-correlations of trading volumes. For general reviews of the statistical properties of financial markets see, for instance, Mantegna and Stanley (2000), Cont (2001), Lux and Ausloos (2002) or Sornette (2003).

In the following, to avoid time zone and currency differences, our exposition mainly rests on the behavior of the stock indices of Germany (DAX30) and France (CAC40). However, we also take those of the United Kingdom (FTSE100), Spain (IBEX35), the Unites States (S&P500) and Japan (NIKKEI225) into account. All six time series range from January 1, 1988 to December 31, 2012 and consist of 6522 daily observations. The data was downloaded from Thomson Reuters Datastream.

Figures 1 and 2 illustrate the behavior of the DAX30 and the CAC40, respectively. The top panels show the evolution of their daily quotes. Note that both stock markets display significant bubbles and crashes. For instance, we observe strong price appreciations between March 2003 and July 2007. Over this period, the DAX30 (CAC40) rose from 2202.96

(2403.04) to 8105.69 (6125.60) points. After July 2007, however, prices began to drop sharply. In March 2009, the price of the DAX30 (CAC40) fell below 3667 (2520) points, losing about 55 (59) percent of its value. A detailed historical account of stock market bubbles and crashes can be found in Kindleberger (2000) and Shiller (2005).

[Figures 1 and 2 about here]

Another characteristic feature of stock markets is that of excessive price volatility. The second panels of figures 1 and 2 display daily returns of the DAX30 and the CAC40 over the same time horizon as in the first panels. Apparently, prices fluctuate strongly and extreme price changes of the DAX30 (CAC40) reach up to 14 (11) percent. To measure volatility, we follow Guillaume et al. (1997) and compute the average absolute return, which reveals an astonishing value of V=1.02 (V=1.00) percent per day for the German (French) stock index. As argued by Shiller (1981), such volatility levels appear to be too large to be driven by fundamental shocks only.

A third stylized fact concerns the distribution of returns and its fat tail property. Evidence for this statistical feature is presented in the central panels of figures 1 and 2. On the left-hand sides, the probability density functions of the empirical DAX30 and CAC40 returns (thick lines) are compared with those of normally distributed returns with identical means and standard deviations (thin lines). The distributions of empirical returns possess a higher concentration around the means, thinner shoulders, and again more probability mass in their tails. The latter finding becomes clearly visible on the right-hand sides. Here we plot, on a log-log scale, the cumulative distributions of normalized DAX30 and CAC40 returns together with the cumulative distribution of standard normally distributed returns (the empirical returns are normalized by dividing by their standard deviations). One way to quantify the fat tail property is to estimate the so-called tail index α, given as $F(|return| > x) \approx cx^{-\alpha}$. Note that lower values for α imply less steep slopes of the cumulative distributions and thus fatter tails.

Regressions on the largest 30 percent of the observations yield a tail index equal to 3.65 for the DAX30 and a value of 3.58 for the CAC40. Lux and Ausloos (2002) determine similar values for other stock markets and other periods. Usually, the tail index ranges between 3 and 4.

As already noted by Bachelier (1900), the price dynamics of speculative markets closely resembles a random walk. In the penultimate panels of figures 1 and 2, the autocorrelation functions for raw returns are depicted for the first 100 lags. Since the dotted lines illustrate 95 percent confidence bands, based on the assumption of a white noise process, both return time series show correlation coefficients that are not significant for nearly all lags. Despite the presence of bubbles and crashes, it remains difficult to predict the future direction of stock markets.

A quite intriguing phenomenon of stock markets is that periods of high volatility alternate with periods of low volatility (Mandelbrot 1963). The volatility clustering of the DAX30 and CAC40 is already obvious from the second panels of figures 1 and 2. However, temporal persistence in volatility can also be seen in the bottom panels of figures 1 and 2, showing the autocorrelation functions of absolute returns. Both absolute return time series reveal autocorrelation coefficients that are significant for more than 100 lags.

The next two stylized facts are presented in figure 3. To illustrate the high level of comovements of international stock markets, the evolution of the German stock market index (black line) and of the French stock market index (gray line) are shown in the top panel of figure 3 (both time series have been normalized by their mean). Note that while the two stock markets may disconnect for some time, they always align with each other soon afterwards. Forbes and Rigobon (2002) conclude that such stock market comovements are a very robust phenomenon and do not only happen in particular crisis periods. The penultimate panel of figure 3 contains the cross-correlation function of raw returns for time differences up to ±50 lags. As can be seen, the contemporaneous correlation between the two European stock indices is high, with a correlation coefficient equal to 0.79. In contrast, the coefficients on almost all other lags show correlations that are not significant. For Shiller (1989), such strong comovements of international stock markets cannot be explained by fundamentals.

[Figure 3 about here]

In the remaining panels of figure 3, the cross-correlation of stock market volatility is exemplified. The second and third panels contain normalized returns of the DAX30 and the CAC40, i.e. both return time series have been divided by their standard deviation. Obviously, the normalized returns of the two time series evolve quite similarly. In both panels, for instance, volatility is low between 2005 and 2006 and the period around 2009 can be regarded as highly volatile. The bottom panel of figure 3 shows the cross-correlation function of absolute returns. While the cross-correlation coefficient again exhibits a high value on lag 0 of about 0.73, the lagged correlations now contrast strongly with those in raw returns. The cross-correlation coefficients of absolute returns are clearly positive and decline slowly with a higher lag difference. Similar results are reported by Edwards and Susmel (2001) and Podobnik et al. (2007), for instance, for other stock markets.

Due to the many degrees of freedom in defining, measuring and, in particular, detrending stock market trading volumes (see Lo and Wang 2010 for a comprehensive survey), we abstain from giving a detailed presentation of the stylized facts concerning trading volumes of stock markets and how they relate to volatility. Although results in this area vary to some degree due to the aforementioned reasons, the following picture emerges. Stock market trading volume is highly persistent, i.e. autocorrelation coefficients for trading volume are positive and decay rather slowly (Bollerslev and Jubinsky 1999, Lobato and Velasco 2000 and Lux and Kaizoji 2007). Moreover, stock market trading volume is positively correlated with volatility (Karpoff 1987 or Gallant et al. 1992). For instance, Brock and LeBaron (1996), who study weekly IBM and CRSP data, find a strong contemporaneous correlation between stock market trading volume and volatility. However, the observed correlation drops quickly for lower and higher lags. Since trading volume is correlated with volatility and since volatility is correlated across markets, trading volume must also be correlated across markets. Indeed, Lee and Rui (2002) show that US trading volume is positively related to trading volumes of UK and Japanese markets.

Tables 1 and 2 extend the empirical evidence. Table 1 presents estimates for five univariate stylized facts, taking DAX30, CAC40, FTSE100, IBEX35, S&P500 and NIKKEI225 data into account. Accordingly, the average values of absolute returns range between 0.78 and 1.06 percent per day. Due to unobservable fundamentals, we cannot quantify stock market distortions. Estimates of the tail index vary between 3.20 and 3.70, i.e. the distributions of returns of all six stock markets possess fat tails. Whereas almost all correlation coefficients for raw returns are non-significant, there is clear evidence for temporal dependence in volatility. Correlation coefficients of absolute returns achieve values up to 0.23 on the first lag and still reveal values between 0.07 and 0.11 on lag 100.

[Table 1 and 2 about here]

Table 2 is concerned with two bivariate stylized facts. Comovements of stock prices and cross-correlations of volatilities are quantified by estimates of the cross-correlation function of raw and absolute returns, respectively. To avoid the problem of nonsynchronous trading, we take only the six possible pairwise combinations of our four European indices into account. While the coefficient for a contemporaneous correlation in raw returns exhibits a mean value of 0.75, the other coefficients computed on a basis of a lag of ±1 reveal values that are not significant. Cross-correlation coefficients of absolute returns range between 0.61 and 0.73 on lag 0. The long-range behavior of correlations in absolute returns can also be identified for the other time series combinations. Coefficients reach values up to 0.28 on a ±1 lag difference and decay to values varying between 0.09 and 0.14 when their estimate is based on a time difference of ±50 lags.

3 Heterogeneous speculators and interacting stock markets

In this section, we introduce a simple agent-based financial market model in which speculators trade on the basis of technical and fundamental analysis in two stock markets. We start this section by describing our motivation and by giving an overview of the structure of our model. In Section 3.2, we reveal the details of our model. Since our model contains a larger number of parameters, we introduce some simplifying symmetry conditions in Section 3.3, which also includes comments on our basic parameter setting.

3.1 Motivation and overview

The goal of our paper is to develop an agent-based financial market model which is capable of generating realistic stock market dynamics, i.e. we seek to match the complete set of stylized facts outlined in the previous section. As far as we know, no other model can jointly explain all these statistical regularities. In particular, current agent-based models find it difficult to produce comovements of stock prices and volatility correlations. In brief, the structure of our model may be summarized as follows. We consider two stock markets which are populated by market makers and heterogeneous speculators. The stock markets are located in two different countries and, for simplicity, we assume that the countries either share the same currency or have agreed upon a fixed exchange rate. The task of market makers is to mediate transactions. Moreover, they adjust prices with respect to excess demands in the usual way. Speculators, in turn, rely on technical and fundamental trading rules to determine their orders. Since speculators can choose between two stock markets and two trading philosophies, they have, in total, four trading alternatives. According to technical analysis, prices move in trends, and buying (selling) is recommended when prices increase (decrease). Fundamental analysis predicts that prices will return towards their fundamental values. In undervalued markets, fundamental trading rules suggest buying and in overvalued markets they propose selling. All four trading alternatives incorporate noise. On the one hand, speculators experience idiosyncratic shocks. On the other hand, speculators are subject to trading rule-specific, market-wide and global shocks. As a result, orders placed by speculators are correlated. In each time step, all speculators have to select one of the four trading alternatives, whereby their choices are influenced by three socio-economic principles. Speculators may have a behavioral bias for one of their trading alternatives, are subject to herding behavior, and evaluate current market circumstances. Simulations, presented in Section 4, reveal that this setup is able to produce realistic stock price dynamics.

3.2 A simple agent-based approach

Let us turn to the details of our model. Stock prices in markets X and Z are adjusted by market makers who collect all individual orders from speculators and change stock prices with respect to the resulting excess demands. Following Day and Huang (1990), we express the behavior of market makers as

$$P_{t+1}^{X} = P_t^{X} + a^{X}(NW_t^{XC}D_t^{XC} + NW_t^{XF}D_t^{XF}), \tag{1}$$

and

$$P_{t+1}^{Z} = P_t^{Z} + a^{Z}(NW_t^{ZC}D_t^{ZC} + NW_t^{ZF}D_t^{ZF}), \tag{2}$$

where P_t^X and P_t^Z are the log stock prices at time step t in markets X and Z, a^X and a^Z are positive price adjustment parameters in markets X and Z, N captures the total number of speculators, W_t^{XC} and W_t^{ZC} are the market shares of chartists in markets X and Z, D_t^{XC} and D_t^{ZC} are the orders placed by (single) chartists in markets X and Z, W_t^{XF} and W_t^{ZF}

are the market shares of fundamentalists in markets X and Z, and D_t^{XF} and D_t^{ZF} are the orders placed by (single) fundamentalists in markets X and Z. Obviously, market makers quote higher stock prices in case of excess buying and decrease stock prices in case of excess selling.

Technical analysis seeks to filter trading signals out of past price movements (Murphy 1999). Although the unifying philosophy of technical analysis is to extrapolate past price trends into the future, there exists a myriad of different technical trading rules. To capture part of the variety of technical analysis, Westerhoff and Dieci (2006) propose formalizing technical trading via a deterministic and a stochastic component. Accordingly, the orders placed by chartists in markets X and Z are given by

$$D_t^{XC} = c^X (P_t^X - P_{t-1}^X) + S_t^{XC} \tag{3}$$

and

$$D_t^{ZC} = c^Z (P_t^Z - P_{t-1}^Z) + S_t^{ZC}\,. \tag{4}$$

Since c^X and c^Z are positive reaction parameters, the first components in the above trading rules imply that chartists go with the current stock price trend. The second components in (3) and (4), denoted by S_t^{XC} and S_t^{ZC}, are random variables that capture all digressions from the first deterministic components. These random terms will be explained in the sequel.

Fundamental analysis presumes that stock prices revert towards their fundamental values in the long run (Graham and Dodd 1951). Fundamental analysis thus recommends buying undervalued assets and selling overvalued assets. Let $\overline{P}^X$ and $\overline{P}^Z$ stand for the (constant) log fundamental values of stock markets X and Z, respectively. Taking again digressions from this core principle into account, we specify the orders placed by fundamentalists in these two markets as

$$D_t^{XF} = f^X(\overline{P}^X - P_t^X) + S_t^{XF} \tag{5}$$

and

$$D_t^{ZF} = f^Z(\overline{P}^Z - P_t^Z) + S_t^{ZF}. \tag{6}$$

Reaction parameters f^X and f^Z are positive, indicating the strength with which fundamentalists react to observed mispricings; random variables S_t^{XF} and S_t^{ZF} summarize all other influences that have an impact on fundamentalists.

In Westerhoff and Dieci (2006), the random terms in trading rules (3) to (6) are independent. As a result, their model is neither able to produce comovements of stock prices nor cross-correlations of volatilities. In our paper, we abolish this simplifying assumption. To be precise, we assume that the random terms S_t^{XC}, S_t^{ZC}, S_t^{XF} and S_t^{ZF} aggregate the effects of four different types of shock:

- Idiosyncratic shocks reflect the diversity of actual technical and fundamental trading rules. Note that speculators may vary their trading intensities with respect to their trading signals, chartists may experiment with different lag lengths when they determine price trends, fundamentalists may alter their perceptions of the fundamental values, and so on. Idiosyncratic shocks may be regarded as a convenient shortcut to be able to abstain from modeling such complexities in more detail.
- Market-wide shocks capture local phenomena. Speculators in market X, regardless of whether they apply technical or fundamental trading rules, may, for instance, be influenced by the same local policy rumors or by the same local business gossip. Of course, such sources of local noise also exist in market Z, and it is difficult to imagine that speculators' trading decisions do not depend on them.
- Trading rule-specific shocks collect influence factors that either matter for technical trading or for fundamental trading, irrespective of the markets in which speculators apply them. One

example of this is the investment advice given by gurus with either having chartist or fundamentalist attitudes, who proclaim global buying or selling opportunities. Sentiment waves restricted to certain trader types are another example of trading rule-specific shocks.

- General shocks are shocks that affect all speculators in all markets alike. For instance, certain global developments may render the investment mood of speculators around the world either optimistic or pessimistic. In fact, all speculators are primed, via common newspapers, international broadcasting or modern media, by the same set of information.

Formally, random variables S_t^{XC}, S_t^{ZC}, S_t^{XF} and S_t^{ZF} are constructed as

$$S_t^{XC} = I_t^{XC} + M_t^X + R_t^C + G_t , \tag{7}$$

$$S_t^{ZC} = I_t^{ZC} + M_t^Z + R_t^C + G_t , \tag{8}$$

$$S_t^{XF} = I_t^{XF} + M_t^X + R_t^F + G_t \tag{9}$$

and

$$S_t^{ZF} = I_t^{ZF} + M_t^Z + R_t^F + G_t . \tag{10}$$

We assume that all random variables on the right-hand side of (7) to (10) are independently normally distributed with zero means and constant variances. Idiosyncratic shocks are denoted by $I_t^{XC} \sim N(0, \sigma_I^{XC})$, $I_t^{ZC} \sim N(0, \sigma_I^{ZC})$, $I_t^{XF} \sim N(0, \sigma_I^{XF})$ and $I_t^{ZF} \sim N(0, \sigma_I^{ZF})$, market-wide shocks by $M_t^X \sim N(0, \sigma_M^X)$ and $M_t^Z \sim N(0, \sigma_M^Z)$, rule-specific shocks by $R_t^C \sim N(0, \sigma_R^C)$ and $R_t^F \sim N(0, \sigma_R^F)$ and general shocks by $G_t \sim N(0, \sigma_G)$.

Before we continue with a description of our model, a number of aspects deserve greater attention:

- Aggregate shocks S_t^{XC}, S_t^{ZC}, S_t^{XF} and S_t^{ZF} are obviously normally distributed with zero means and constant variances. As we will see in Section 4, stock prices fluctuate symmetrically around their fundamental values, i.e. periods of undervaluation are as pronounced as periods of overvaluation. Assuming that the means of aggregate shocks are positive, say, due to some general kind of optimism, this would break the symmetry and create more positive than negative bubbles.

- Variances of the nine shock components are identified by calibrating our model, i.e. we let the data decide which components are more important and which are less important. Compared to Karolyi and Stulz (1996), who seek to explain cross-country stock market comovements by the interplay of idiosyncratic shocks, competitive (market-wide) shocks and global shocks, we also take rule-specific shocks into account. As in their case, we assume that the shock components are uncorrelated and additively aggregated.
- Variances of the nine shock components determine the correlation structure between S_t^{XC}, S_t^{ZC}, S_t^{XF} and S_t^{ZF}. Roughly speaking, the stronger the idiosyncratic shocks, the lower the correlation between S_t^{XC}, S_t^{ZC}, S_t^{XF} and S_t^{ZF}. The opposite effect emerges when the global shock component becomes more important. An increase in variances of market-wide shocks increases the correlation between S_t^{XC} and S_t^{XF} and between S_t^{ZF} and S_t^{ZC}, while an increase in variances of rule-specific shocks increases the correlation between S_t^{XC} and S_t^{ZC} and between S_t^{ZF} and S_t^{XF}. In Appendix 1, we derive analytically the variance-covariance matrix and the correlation matrix of the aggregate shocks.
- While aggregate shocks and their correlation structure play a crucial role in our model, any model in which market shares are fixed will fail to explain the dynamics of real stock markets. For instance, if our model has fixed market shares, it is unable to produce fat tails or persistence in volatility and trading volume. As will become clear in Section 4, a realistic model dynamics emerges from the interplay between endogenous (nonlinear) forces and exogenous (correlated) shocks.

- Our modeling of speculators' trading behavior neglects a number of potentially important issues. In particular, speculators ignore gains from diversification and may build up substantial (positive or negative) stock positions. However, Tesar and Werner (1994) report that the hypothesis that investors follow the CAPM in their portfolio allocations is strongly rejected by the data. In this respect, see also Lewis (1999) or Karolyi and Stulz (2003). Moreover, Franke and Asada (2008) show that the dynamics of agent-based financial market models may not change much if one allows speculators to manage their inventory. From this perspective, our modeling of speculators' trading behavior may be regarded as acceptable.

In each time step, speculators have to decide which trading rule to follow in which market. Based on the estimated agent-based financial market model of Franke and Westerhoff (2012), it seems that speculators have a behavioral preference towards technical analysis, and that they tend to follow the crowd and increasingly switch towards fundamental analysis when stock prices move away from their fundamental values. Therefore, we define the attractiveness of speculators' four trading options as

$$A_t^{XC} = b^{XC} + h^{XC} W_{t-1}^{XC} - d^{XC} | \overline{P}^X - P_{t-1}^X |, \tag{11}$$

$$A_t^{ZC} = b^{ZC} + h^{ZC} W_{t-1}^{ZC} - d^{ZC} | \overline{P}^Z - P_{t-1}^Z |, \tag{12}$$

$$A_t^{XF} = b^{XF} + h^{XF} W_{t-1}^{XF} + d^{XF} | \overline{P}^X - P_{t-1}^X | \tag{13}$$

and

$$A_t^{ZF} = b^{ZF} + h^{ZF} W_{t-1}^{ZF} + d^{ZF} | \overline{P}^Z - P_{t-1}^Z |. \tag{14}$$

Note that the behavioral bias of speculators for or against certain trading alternatives can be expressed by parameters b^{XC}, b^{ZC}, b^{XF} and b^{ZF}. For instance, a scenario with $b^{XC} > 0$ and $b^{ZC} = b^{XF} = b^{ZF} < 0$ implies that speculators have a preference towards technical trading in market X and an equally strong aversion against all other options. Since speculators tend to follow the crowd, the attractiveness of a trading rule increases with the size of its market share. Parameters h^{XC}, h^{ZC}, h^{XF} and h^{ZF} are positive, capturing the strength of speculators' herding behavior. Finally, speculators can assess market circumstances. While speculators believe that bubbles are persistent, they are also aware that every bubble will eventually burst. In particular, speculators perceive a higher probability that a fundamental price correction is about to set in if the price deviates from its fundamental value. How sensitively the attractiveness of the four trading alternatives reacts to distortions is controlled by parameters d^{XC}, d^{ZC}, d^{XF} and d^{ZF}.[1]

The market shares of speculators following technical analysis in market X, technical analysis in market Z, fundamental analysis in market X and fundamental analysis in market Z depend on their relative attractiveness. Following Brock and Hommes (1998), we use the discrete choice approach to determine these market shares, and obtain

$$W_t^{XC} = \frac{Exp[rA_t^{XC}]}{Exp[rA_t^{XC}] + Exp[rA_t^{ZC}] + Exp[rA_t^{XF}] + Exp[rA_t^{ZF}]}, \tag{15}$$

$$W_t^{ZC} = \frac{Exp[rA_t^{ZC}]}{Exp[rA_t^{XC}] + Exp[rA_t^{ZC}] + Exp[rA_t^{XF}] + Exp[rA_t^{ZF}]}, \tag{16}$$

$$W_t^{XF} = \frac{Exp[rA_t^{XF}]}{Exp[rA_t^{XC}] + Exp[rA_t^{ZC}] + Exp[rA_t^{XF}] + Exp[rA_t^{ZF}]}, \tag{17}$$

and

$$W_t^{ZF} = \frac{Exp[rA_t^{ZF}]}{Exp[rA_t^{XC}] + Exp[rA_t^{ZC}] + Exp[rA_t^{XF}] + Exp[rA_t^{ZF}]}. \tag{18}$$

Parameter $r > 0$ is a so-called sensitivity of choice parameter that measures how sensitively the mass of speculators reacts to differences in the attractiveness of trading rules. If, for

[1] Franke and Westerhoff (2012) use squared deviations of log prices and log fundamental values to capture the misalignement effect. Absolute deviations seem to do a better job in our simulations. Note that Brock and Hommes (1998) interpret behavioral bias parameters as information-gathering cost parameters. Furthermore, they focus on past realized profits as the main fitness criterion.

instance, the attractiveness of fundamental analysis in market X increases, then the market share of this rule increases too – at the expense of the market shares of the three other rules. The higher parameter r, the greater the increase in the market share of fundamental analysis in market X will be. In this sense, we also regard parameter r as a rationality parameter.

3.3 Simplifications and basic parameter setting

Our general model incorporates a large number of parameters. Note, however, that the two price adjustment parameters, the population size of speculators and the rationality parameter are scaling parameters. Without loss of generality, we thus fix $a_X = a_Z = 0.01$, $N = 1$ and $r = 1$. Moreover, the levels of (constant) log fundamental values do not influence the model dynamics and for this reason we set $\overline{P}^X = \overline{P}^Z = 0$.

For simplicity, and to reduce the number of parameters further, we introduce a few symmetry conditions. We assume that chartists' reaction parameters in markets X and Z are equal, i.e. $c = c^X = c^Z$, and that the same is true for fundamentalists' reaction parameters, i.e. $f = f^X = f^Z$. Similarly, the levels of idiosyncratic shocks of the two technical trading rules and of the two fundamental trading rules are identical across markets, i.e. $\sigma_I^C = \sigma_I^{XC} = \sigma_I^{ZC}$ and $\sigma_I^F = \sigma_I^{XF} = \sigma_I^{ZF}$. As a result, the average trading intensity of a chartist (fundamentalist) active in market X is comparable to the average trading intensity of a chartist (fundamentalist) in market Z. With respect to predisposition, herding and misalignment parameters, we assume that $b = b^{XC} = b^{ZC}$, $0 = b^{XF} = b^{ZF}$, $h = h^{XC} = h^{ZC} = h^{XF} = h^{ZF}$ and $d = d^{XC} = d^{ZC} = d^{XF} = d^{ZF}$. This implies that speculators may have a behavioral bias towards technical analysis ($b > 0$) or towards fundamental analysis ($b < 0$), yet they do not discriminate between trading rules across markets.[2] Moreover, herding effects and market distortions have the same consequences across all four of the speculators' options.

Overall, 12 parameters remain to be specified. After an extended trial-and-error calibration exercise, we arrived at the following parameter setting

$$c = 2.00,\ f = 0.10,\ b = 0.75,\ h = 2.35,\ d = 2.20$$

$$\sigma_I^C = 0.72,\ \sigma_I^F = 0.02,\ \sigma_M^X = 0.20,\ \sigma_M^Z = 0.20,\ \sigma_R^C = 2.95,\ \sigma_R^F = 0.10,\ \sigma_G = 0.35.$$

Accordingly, the reaction parameters of the deterministic cores of technical and fundamental trading rules are both positive. Moreover, speculators have a behavioral preference for technical analysis, they are subject to herding behavior and turn to fundamental analysis as prices diverge from fundamental values. The interpretation of the random shock components is more complicated, and can be found in Appendix 1. In the absence of exogenous shocks, the deterministic skeleton of our calibrated model possesses a unique steady state in which prices mirror their fundamental values and in which the majority of speculators opts for technical analysis. To be precise, 41 percent of speculators rely on technical analysis in market X, 41 percent on technical analysis in market Z, 9 percent on fundamental analysis in market X and 9 percent on fundamental analysis in market Z. Of course, this asymmetry results from traders' predisposition and herding behavior.

While a certain amount of progress has been made with respect to estimating small-scale agent-based models over the last couple of years (Gilli and Winker 2003, Alfarano et al. 2005, Boswijk et al. 2007, Manzan and Westerhoff 2007, Franke and Westerhoff 2012), the complexity of our model with its two markets, 12 parameters and 10 stylized facts prevents us from estimating it. However, our model is able to mimic a number of important statistical properties of stock markets, as we will see in the next section.

---

[2] If speculators do not discriminate between markets, only the difference in predisposition parameters matter. Since we focus on this case, we can set b^{XF} and b^{ZF} to zero.

4 Simulation analyses

Before we explain how our model functions, we show the extent to which our model is able to replicate the statistical properties of and between international stock markets. In this respect, we will first explore a representative simulation run, depicted in figures 4 to 6, and then turn to a more thorough Monte Carlo analysis. The simulation run contains 6500 (daily) observations and thus mirrors a period of about 25 years. Since the design of figures 4 to 6 is identical to that of figures 1 to 3, our simulations can be compared directly with the performance of the DAX30 and the CAC40.

Let us start with figures 4 and 5. Their top panels show the development of stock prices in markets X and Z, respectively. In the long run, prices fluctuate around their fundamental values. Temporarily, however, our model is able to generate substantial bubbles. Between periods 1200 and 1700, for instance, we observe sharp price appreciations with stock prices deviating more than 50 percent from fundamentals. In our model, such bubbles may deflate or crash. The second panels of figures 4 and 5 exhibit the evolution of the corresponding returns. On average, price volatility is high and extreme daily price changes occasionally exceed the 10 percent level. The two central panels of figures 4 and 5 characterize the distributions of simulated returns (thick lines) and normally distributed returns (thin lines). As can be seen, the distributions of simulated returns deviate significantly from a Normal distribution and possess fat tails. The last two panels of figures 4 and 5 exemplify the autocorrelation functions of raw and absolute returns, respectively. While raw returns are essentially unpredictable, absolute returns display significant long memory effects.

[Figures 4 and 5 about here]

Figure 6 presents linkages between stock markets X and Z. The top panel shows the paths of normalized stock prices in markets X (black line) and Z (gray line). Stock prices move closely together most of the time, although there are also intermediate periods where the two stock markets display a life of their own (see, for example, the dynamics between time steps 2200 and 3300). In fact, the cross-correlation function of raw returns, visualized in the penultimate panel, reveals a strong contemporaneous correlation between the two stock markets. As in reality, all other cross-correlation coefficients are not significant. The second and third panels of figure 6 suggest that the magnitudes of normalized returns of stock markets X and Z are correlated. This observation is supported by the bottom panel. The cross-correlation function of absolute returns reveals not only a high coefficient for lag 0 of about 0.65 but also significant coefficients for lag sizes of up to ±50.

[Figure 6 about here]

Figure 7 presents a number of properties of simulated trading volumes and how they relate to volatility. The first and second panels show the evolution of trading volume in stock markets X and Z, respectively. Obviously, trading volume is persistent and correlated across markets. The third panel quantifies the long memory behavior of trading volume. Autocorrelation coefficients of trading volume in market X are positive and decay slowly with an increasing lag length. The cross-correlation of trading volumes of markets X and Z is portrayed in the penultimate panel. Cross-correlation coefficients exhibit a value of 0.68 for lag 0 and much lower values for lags up to ±50. Finally, the cross-correlations of trading volume and absolute returns of market X are depicted in the bottom panel. Computations reveal a strong positive contemporaneous correlation between trading volume and volatility, whereas lagged correlations are still significant but much lower.[3]

[Figure 7 about here]

To sum up so far, properties of the simulation run presented in figures 4 to 6 resemble the behavior of actual data presented in figures 1 to 3 remarkably well. In addition, our model also seems to match, at least in a qualitative sense, basic features of trading volume and its

[3] Since stock markets X and Z are symmetric, we abstain from showing autocorrelations in volume and cross-correlations between volume and volatility for stock market Z.

relation to volatility. To check the robustness of these results, we next perform a Monte Carlo study. Our analysis rests on 5000 simulation runs, each containing 6500 observations. All simulation runs are based on the same parameter setting but differ in their seeds of random variables. Tables 3 and 4 contain the same univariate and bivariate statistics as in tables 1 and 2. We report estimates of the mean and the 5, 25, 50, 75 and 95 percent quantiles of these statistics. Due to the stock markets' symmetry, we restrict the analysis of univariate statistical properties to one market.

Table 3 reveals, for instance, that the model's average volatility (0.83) is in line with real market observations. Moreover, estimates of the distortion, measured as the average absolute deviation between stock prices and fundamentals, hover between 21.97 and 31.21 percent in 90 percent of the cases. Hence, there are substantial boom-bust cycles in almost all simulation runs. To reduce computational efforts, we now use the Hill tail index estimator to estimate the tail index (Hill 1975).[4] Taking the largest 5 percent of observations into account, we obtain tail indices equal to 3.11 and 3.48 for the lower and upper quartile. Note that the tail indices reported in table 1 for real data, ranging between 3.20 and 3.65, are quite close to these numbers. Quite importantly, autocorrelation coefficients of simulated raw returns indicate that price increments are basically uncorrelated. As in reality, it is difficult to predict the future direction of stock markets. Moreover, autocorrelation coefficients for absolute returns show a median value of 0.25 for the first lag. While our model may slightly exaggerate the autocorrelation of absolute returns for the first lag (25 percent of our simulation runs display autocorrelation coefficients above 0.27), it seems to match the other autocorrelation coefficients fairly well.

[Table 3 and 4 about here]

---

[4] Application of the Hill tail estimator, derived as $\alpha = \left(\frac{1}{k} \sum_{i=1}^{k} LogX_{T-i+1} - LogX_{T-k} \right)^{-1}$, requires sample elements to be placed in descending order: $X_T \succ X_{T-1} \succ ... \succ X_{T-k} \succ ... \succ X_1$. Parameter k enables us to determine the number of observations located in the tail.

Table 4 is concerned with statistical properties between stock markets X and Z. Estimates of the contemporaneous cross-correlation of simulated raw returns exhibit a value of 0.75 for the 5 percent quantile and 0.85 for the 95 percent quantile while the corresponding cross-correlation coefficients for lags ±1 are not significant. Therefore, we conclude that our model generates realistic comovements between stock markets. Note that absolute returns reveal a median cross-correlation of 0.65 for lag 0, which is quite close to real data observations. However, cross-correlation coefficients of absolute returns for lags ±1 display values less than 0.16 in 75 percent of simulations. Since cross-correlation coefficients of our empirical time series range between 0.18 and 0.28, our model fails to replicate the exact magnitude of empirical cross-correlations of volatilities for lags ±1. While the matching results of cross-correlation coefficients with lags of ±25 are somewhat mixed, we note that cross-correlation coefficients for lags of ±50 again correspond well with those obtained from empirical data.

Overall, our simple agent-based financial market model seems to have a remarkable ability to reproduce the univariate and bivariate stylized facts presented in section 2 – which raises the questions how our model functions and what we can learn from it. To answer these questions, figure 8 presents a subsample of our initial simulation run. The selected time window ranges from period 1000 to period 2500, and covers about 6 years. The top (second) and bottom (penultimate) panels contain trajectories of simulated stock prices (price changes) in markets X and Z, respectively. The market shares of the four trading strategies are plotted in the central panel. From top to bottom, this panel shows the weights of chartists in market X (black), fundamentalists in market X (white, above gray line), fundamentalists in market Z (white, below gray line) and chartists in market Z (black).

[Figure 8 about here]

Due to the symmetry of stock markets X and Z, speculators are spread, on average, evenly across markets. Further computations reveal that around 30 percent of speculators rely on technical analysis, while 70 percent apply fundamental analysis. More importantly, however, there is a permanent evolutionary competition between stock markets and trading strategies. There may be periods where there are more speculators in market X than in market Z, or the other way around. Similarly, no particular strategy vanishes from one of the markets, nor does a particular strategy dominate all markets forever. As we will see, it is the recurrent up and down movements of the market shares of the four trading strategies that drive the model dynamics.

Let us study figure 8 in more detail. Initially, both stock markets are strongly undervalued and most speculators opt for fundamental trading. Fundamentalists' buying orders result in positive excess demands, and market makers increase stock prices towards more moderate levels. The reduction of mispricing, in turn, renders fundamental analysis less attractive and, consequently, more and more speculators turn to technical analysis. Around period 1200, chartists eventually dominate both stock markets. Recall from Appendix 1 that chartists tend to speculate much more aggressively than fundamentalists. The trading behavior of chartists thus leads to an increase in trading volumes and volatilities, and stock prices start to overshoot their fundamental values. Roughly 300 periods later, the bubbles lose their momentum. Due to strong overvaluations of the stock markets, speculators now perceive fundamental analysis as more attractive and return to fundamental trading. Both stock markets enter a period of relative stability: trading volumes, volatilities and mispricings decline over time – until chartists regain control of the stock markets and create a new period of instability.

There are two reasons why regime changes from a dominance of fundamentalism to a dominance of chartism, and vice versa, may persist. Consider the case of a developed bubble in which most speculators have already turned to fundamental analysis. First of all, the aggressiveness of fundamentalists' mean reversion trading, expressed by parameter $f = 0.10$, is rather weak. Since fundamentalists' trading behavior (as well as that of the remaining chartists) contains a random component, the bubble may only evaporate slowly, implying that the attractiveness of fundamental analysis tends to remain high. Moreover, this effect is supported by speculators' herding behavior. The more followers a trading strategy has, the more attractive speculators consider it to be. The fundamental regime thus benefits from its own popularity. But once fundamental trading has reduced mispricing sufficiently strongly, speculators start to switch to technical analysis. This regime change is fueled by speculators' behavioral preference for technical analysis. In the aftermath of such a regime change, predisposition effects and herding behavior may jointly establish a lasting dominance of technical analysis. Since chartists trade, on average, more aggressively than fundamentalists, the persistence of technical and fundamental trading regimes causes a long memory of trading volume and volatility, and leads to a significant cross-correlation between trading volume and volatility.

Despite the lasting boom-bust phases of stock markets, the evolution of stock prices is close to a random walk. By amplifying price trends, technical trading tends to trigger bubbles. Fundamental trading, in turn, induces long-run mean reversion, and may therefore stop bubbles. However, speculators' trading behavior contains a significant random element, which keeps day-to-day price changes uncorrelated. Since fundamental and technical trading regimes may be short or long lived, the size and length of bubbles are hard to predict. Naturally, given that fundamental values are constant, all these price fluctuations imply excess volatility.

An important implication of our calibrated model is that the two stock markets display a strong and robust coevolution, with respect to not only their price levels, but also their trading volumes and volatilities. But what causes the synchronization of stock markets?

Recall first that speculators' orders are correlated across markets. Since market makers adjust prices with respect to excess demands, price changes are partially aligned. However, this is not the end of the story. Due to the partial alignment of stock prices, speculators perceive the attractiveness of stock markets as being not very dissimilar. As a result, speculators distribute more or less evenly across stock markets X and Z, meaning that if stock market X possesses a large number of chartists (fundamentalists), stock market Z also possesses a large number of chartists (fundamentalists). Obviously, this effect considerably strengthens the coevolution of prices and also evokes significant cross-correlations in trading volumes and volatilities. Without such a synchronization of market shares, the model would clearly lose its ability to generate realistic stock market interactions. Consider, for instance, the opposite case in which stock market X is dominated by chartists while stock market Z is dominated by fundamentalists. We would then observe a period of high volatility in stock market X with prices diverging from fundamental values. In contrast, stock market Z would be characterized by a period of low volatility and a convergence of prices towards fundamental values.

Now and then, however, the strong coevolution of stock markets breaks down as, for instance, between periods 2100 and 2500. Around that time, more than 50 percent of speculators use technical analysis in market Z. If they receive a strong trading signal, extreme price changes of about 10 percent may emerge. The situation may become even more wild when market Z's fundamentalists act upon a correlated trading signal. We learn from this example that interactions between international financial markets, e.g. in the form of a temporary rush of too many speculators into one particular market, may create fat-tailed return distributions and thereby extreme financial market risks.

5 Conclusions

As already pointed out by Shiller (1989), international stock markets display surprisingly strong comovements. In particular, we have repeatedly witnessed simultaneous collapses of major stock markets around the world in the past with serious consequences for real economies. Besides the close coevolution of the price levels of international stock markets, we also observe a significant cross-correlation of their volatilities. To increase our understanding of how such phenomena may emerge, we develop a simple agent-based financial market model. In our model, speculators rely on stochastic technical trading rules and on stochastic fundamental trading rules to determine their orders. While technical analysis advises going with the current stock market trend, fundamental analysis recommends betting on mean reversion. Since speculators are influenced by common factors such as market-wide, rule-specific and general shocks, the stochastic components of their trading rules are correlated. Moreover, speculators switch between trading strategies and stock markets with respect to three socio-economic principles. They may have a behavioral preference for or against certain trading alternatives, they are subject to herding behavior and evaluate current market circumstances. Speculators' transactions are mediated by market makers who adjust prices with respect to the resulting excess demands in the usual way.

Our model is able to replicate a number of prominent univariate stylized facts of financial markets such as bubbles and crashes, excess volatility, fat-tailed return distributions, random walk price dynamics, volatility clustering and persistent trading volume. Concerning individual stock markets, the model dynamics may be outlined as follows. Suppose that prices are close to fundamental values. Speculators then regard fundamental analysis as not particularly appealing. If a sufficient number of speculators turns towards technical analysis, volatility picks up and a bubble is likely to emerge. Such a development then renders the relative attractiveness of trading rules. Since more and more speculators switch to fundamental analysis, volatility decreases and prices return towards fundamental values. Due to speculators' herding behavior, the regimes in which either chartists or fundamentalists dominate the markets are persistent. As a result, we observe substantial long-memory effects in volatility and trading volume.

In addition to this, our model is able to reproduce a number of important bivariate stylized facts of financial markets, including comovements of stock prices, cross-correlations of volatility, cross-correlations of trading volume and temporal dependencies between volatility and trading volume. How do these properties come about? Recall that speculators' transactions are correlated, which induces some basic price comovements. Since speculators therefore perceive the attractiveness of technical analysis and fundamental analysis across markets as being not very different, the relative market impact of technical analysis and fundamental analysis in the two markets becomes synchronized. Of course, this effect strengths the coevolution of stock prices, and triggers the aforementioned cross-correlation properties. Clearly, a model in which the market shares of trading rules are fixed is unable to produce realistic price dynamics. What is needed to obtain realistic dynamics is a synchronized evolution of the relative impact of technical and fundamental analysis in the markets. Note that the synchronization of market shares may occasionally break down. If a sufficient number of speculators decides to rely on technical analysis in one of the markets, we may observe particularly strong price changes. Stock market returns then deviate significantly from what we would expect from normally distributed returns.

In order to obtain a better understanding of what drives the dynamics of and between international stock markets, we tried to keep our model as simple as possible. Finally, we sketch a few directions in which our setup could be extended. First, we assume several symmetric relations within our model, e.g. traders' aggressiveness is equally strong across markets and speculators do not discriminate between periods of overvaluation and undervaluation. Since in real markets we observe more positive than negative bubbles, one may consider adding asymmetries to our model. Second, a further natural extension of our model would be to consider interactions between three stock markets or, maybe as a first step, to consider two international stock markets which are connected via and with a foreign exchange market. Studying the impact of an additional speculative market on the stability of the whole financial system may be particularly interesting from a policy perspective. Third, it would be important to study the consequences of speculative stock market dynamics for the performance of real economies. Having a real economy inside the model would also allow endogenizing the fundamental values of the stock markets. We may then be able to study possible relationships between business cycles and stock market dynamics. Fourth, a major step would be to turn our small-scale agent-based model into a large-scale agent-based model, i.e. to keep track of individual speculators' behavior. Finally, it would be worthwhile finding a more structural approach for dealing with the assumption of correlated stochastic common shocks.

So far we have ignored all these interesting extensions since we consider it important to first develop and understand a simple benchmark model. However, we hope that our paper will stimulate greater effort in this empirically relevant research area. It is surprising how little we know about how the global financial market system really functions.

Appendix 1

The random terms included in speculators' demand functions additively aggregate the effects of idiosyncratic, market-wide, trading rule-specific and general shocks. The latter shock components are uncorrelated and normally distributed. The variance-covariance matrix of the vector of aggregate shocks $S_t = (S_t^{XC}, S_t^{ZC}, S_t^{XF}, S_t^{ZF})'$ can be computed as

$$\Sigma = \begin{pmatrix} V[S_t^{XC}] & (\sigma_R^C)^2 + (\sigma_G)^2 & (\sigma_M^X)^2 + (\sigma_G)^2 & (\sigma_G)^2 \\ (\sigma_R^C)^2 + (\sigma_G)^2 & V[S_t^{ZC}] & (\sigma_G)^2 & (\sigma_M^Z)^2 + (\sigma_G)^2 \\ (\sigma_M^X)^2 + (\sigma_G)^2 & (\sigma_G)^2 & V[S_t^{XF}] & (\sigma_R^F)^2 + (\sigma_G)^2 \\ (\sigma_G)^2 & (\sigma_M^Z)^2 + (\sigma_G)^2 & (\sigma_R^F)^2 + (\sigma_G)^2 & V[S_t^{ZF}] \end{pmatrix}, \tag{A1}$$

where $V[S_t^{XC}] = (\sigma_I^{XC})^2 + (\sigma_M^X)^2 + (\sigma_R^C)^2 + (\sigma_G)^2$, $V[S_t^{ZC}] = (\sigma_I^{ZC})^2 + (\sigma_M^Z)^2 + (\sigma_R^C)^2 + (\sigma_G)^2$, $V[S_t^{XF}] = (\sigma_I^{XF})^2 + (\sigma_M^X)^2 + (\sigma_R^F)^2 + (\sigma_G)^2$ and $V[S_t^{ZF}] = (\sigma_I^{ZF})^2 + (\sigma_M^Z)^2 + (\sigma_R^F)^2 + (\sigma_G)^2$. Accordingly, the correlation matrix of the vector of aggregate shocks results in

$$\rho = \begin{pmatrix} 1 & \frac{(\sigma_R^C)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{XC}]V[S_t^{ZC}]}} & \frac{(\sigma_M^X)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{XC}]V[S_t^{XF}]}} & \frac{(\sigma_G)^2}{\sqrt{V[S_t^{XC}]V[S_t^{ZF}]}} \\ \frac{(\sigma_R^C)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{XC}]V[S_t^{ZC}]}} & 1 & \frac{(\sigma_G)^2}{\sqrt{V[S_t^{ZC}]V[S_t^{XF}]}} & \frac{(\sigma_M^Z)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{ZC}]V[S_t^{ZF}]}} \\ \frac{(\sigma_M^X)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{XC}]V[S_t^{XF}]}} & \frac{(\sigma_G)^2}{\sqrt{V[S_t^{ZC}]V[S_t^{XF}]}} & 1 & \frac{(\sigma_R^F)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{XF}]V[S_t^{ZF}]}} \\ \frac{(\sigma_G)^2}{\sqrt{V[S_t^{XC}]V[S_t^{ZF}]}} & \frac{(\sigma_M^Z)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{ZC}]V[S_t^{ZF}]}} & \frac{(\sigma_R^F)^2 + (\sigma_G)^2}{\sqrt{V[S_t^{XF}]V[S_t^{ZF}]}} & 1 \end{pmatrix}. \tag{A2}$$

For the model's nine shock components, our calibration exercise reveals that $\sigma_I^C = 0.72$, $\sigma_I^F = 0.02$, $\sigma_M^X = 0.20$, $\sigma_M^Z = 0.20$, $\sigma_R^C = 2.95$, $\sigma_R^F = 0.10$ and $\sigma_G = 0.35$. Therefore, we can numerically express the above variance-covariance matrix and the correlation matrix as

$$\Sigma = \begin{pmatrix} 9.383 & 8.825 & 0.163 & 0.123 \\ 8.825 & 9.383 & 0.123 & 0.163 \\ 0.163 & 0.123 & 0.173 & 0.133 \\ 0.123 & 0.163 & 0.133 & 0.173 \end{pmatrix}, \tag{A3}$$

and

$$\rho = \begin{pmatrix} 1.000 & 0.940 & 0.128 & 0.096 \\ 0.940 & 1.000 & 0.096 & 0.128 \\ 0.128 & 0.096 & 1.000 & 0.766 \\ 0.096 & 0.128 & 0.766 & 1.000 \end{pmatrix}, \tag{A4}$$

respectively. The matrices are instructive when it comes to working out how the model functions. For instance, variances of random terms S_t^{XC}, S_t^{ZC}, S_t^{XF} and S_t^{ZF} are given by 9.383, 9.383, 0.173 and 0.173. Putting these numbers into perspective, standard deviations of aggregate shocks entering technical trading rules are about $\sqrt{9.383}/\sqrt{0.173} \approx 7.365$ times larger than those entering fundamental trading rules. This has two important implications. First, the random part of the technical trading rule generates, on average, higher orders than the random part of the fundamental trading rule. Second, chartists trade less systematically than fundamentalists. While technical trading signals may be interpreted quite differently, fundamental analysis seems to be a relatively clear trading concept. Furthermore, the correlation matrix reveals that chartists' transactions in markets X and Z are highly correlated (the correlation coefficient is 0.940). The correlation between these shocks is caused to a large extent by rule-specific shocks. The correlation between fundamentalists' transactions in markets X and Z, given with 0.766, is slightly lower, i.e. fundamentalists also receive relatively similar trading signals across markets. In the case of fundamentalists, however, the correlation is mainly due to global shocks. Finally, the remaining correlation coefficients, capturing relations between chartists in market X (or in market Z) and fundamentalists in market Z (or in market X) are considerably lower. Nevertheless, they are positive and improve the overall matching of the stylized facts.

References

Alfarano, S., Lux, T. and Wagner, F. (2005): Estimation of agent-based models: the case of an asymmetric herding model. Computational Economics, 26, 19-49.

Anufriev, M., Bottazzi, G. Marsili, M. and Pin, P. (2012): Excess covariance and dynamic instability in a multi-asset model. Journal of Economic Dynamics and Control, 36, 1142-1161.

Bachelier, L. (1900): Théorie de la spéculation. Annales scientifiques de l'École Normale Supérieure, 17, 21-86.

Bollerslev, T. and Jubinski, D. (1999): Equity trading volume and volatility: Latent information arrivals and common long-run dependencies. Journal of Business and Economic Statistics, 17, 9-21.

Boswijk, P., Hommes, C. and Manzan, S. (2007): Behavioral heterogeneity in stock prices. Journal of Economic Dynamics and Control, 31, 1938-1970.

Brock, W. and LeBaron, B. (1996): A dynamic structural model for stock return volatility and trading volume. Review of Economics and Statistics, 78, 94-110.

Brock, W. and Hommes, C. (1998): Heterogeneous beliefs and routes to chaos in a simple asset pricing model. Journal of Economic Dynamics Control, 22, 1235-1274.

Brock, W., Hommes, C. and Wagener, F. (2009): More hedging instruments may destabilize markets. Journal of Economic Dynamics and Control, 33, 1912-1928.

Chen, S.-H. and Huang, Y.-C. (2008): Risk preference, forecasting accuracy and survival dynamics: Simulations based on a multi-asset agent-based artificial stock market. Journal of Economic Behavior and Organization, 67, 702-717.

Chiarella, C,. Dieci, R., and Gardini, L. (2002): Speculative behaviour and complex asset price dynamics: A global analysis. Journal of Economic Behavior and Organization, 49, 173-197.

Chiarella, C., Dieci, R. and Gardini, L. (2005): The dynamic interaction of speculation and diversification. Applied Mathematical Finance 12, 17-52.

Chiarella, C., Dieci, R. and He, X.-Z. (2007): Heterogeneous expectations and speculative behaviour in a dynamic multi-asset framework. Journal of Economic Behavior and Organization 62, 408-427.

Chiarella, C., Dieci, R. and He, X.-Z. (2009): Heterogeneity, market mechanisms, and asset price dynamics. In: Hens, T. and Schenk-Hoppé, K.R. (eds.): Handbook of Financial Markets: Dynamics and Evolution. North-Holland, Amsterdam, 277-344.

Chiarella, C., Dieci, R. and He, X.-Z. (2013a): Time-varying beta: a boundedly rational equilibrium approach. Journal of Evolutionary Economics, in press.

Chiarella, C., Dieci, R., He, X.-Z. and Li, K. (2013b): An evolutionary CAPM under heterogeneous beliefs. Annals of Finance, in press.

Cont, R. (2001): Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance, 1, 223-236.

Corona, E., Ecca, S., Marchesi, M. and Setzu, A. (2008): The interplay between two stock markets and a related foreign exchange market: a simulation approach. Computational Economics, 32, 99-119.

Day, R. and Huang, W. (1990): Bulls, bears and market sheep. Journal of Economic Behavior and Organization, 14, 299-329.

De Grauwe, P., Dewachter, H. and Embrechts, M. (1993): Exchange rate theory – chaotic models of foreign exchange markets. Blackwell, Oxford.

Dieci, R. and Westerhoff, F. (2010): Heterogeneous speculators, endogenous fluctuations and interacting markets: a model of stock prices and exchange rates. Journal of Economic Dynamics and Control, 34, 743-764.

Edwards, S. and Susmel, R. (2001): Volatility dependence and contagion in emerging equity markets. Journal of Development Economics, 66, 505-532.

Farmer, D. and Joshi, S. (2002): The price dynamics of common trading strategies. Journal of Economic Behavior and Organization, 49, 149-171.

Feldman, T. (2010): Portfolio manager behavior and global financial crises. Journal of Economic Behavior and Organization, 75, 192-202.

Forbes, K. and Rigobon, R. (2002): No contagion, only interdependence: Measuring stock market comovements. The Journal of Finance, 57, 2223-2261.

Franke, R. (2010): On the specification of noise in two agent-based asset pricing models. Journal of Economic Dynamics and Control, 34, 1140-1152.

Franke, R. and Asada, T. (2008): Incorporating positions into asset pricing models with order-based strategies. Journal of Economic Interaction and Coordination, 3, 201-227.

Franke, R. and Westerhoff, F. (2012): Structural stochastic volatility in asset pricing dynamics: estimation and model contest. Journal of Economic Dynamics and Control, 36, 1193-1211.

Gallant, R., Rossi, P. and Tauchen, G. (1992): Stock prices and volume. The Review of Financial Studies, 5, 199-242.

Gaunersdorfer, A. and Hommes, C. (2007): A nonlinear structural model for volatility clustering. In: Teyssiere, G. and Kirman, A. (eds.): Long Memory in Economics. Springer, Berlin, 265-288.

Gilli, M. and Winker, P. (2003): A global optimization heuristic for estimating agent based models. Computational Statistics and Data Analysis, 42, 299-312.

Graham, B. and Dodd, D. (1951): Security analysis. McGraw-Hill, New York.

Guillaume, D., Dacorogna, M., Davé, R., Müller, U., Olsen, R. and Pictet, O. (1997): From the bird's eye to the microscope: A survey of new stylized facts of the intra-daily foreign exchange markets. Finance Stochastics, 1, 95-129.

Hill, B. (1975): A simple general approach to inference about the tail of a distribution. Annals of Statistics, 3, 1163-1174.

He, X.-Z. and Li, Y. (2007): Power-law behaviour, heterogeneity, and trend chasing. Journal of Economic Dynamics and Control, 31, 3396-3426.

Hommes, C. and Wagener, F. (2009): Complex evolutionary systems in behavioral finance. In: Hens, T. and Schenk-Hoppé, K.R. (eds.): Handbook of Financial Markets: Dynamics and Evolution. North-Holland, Amsterdam, 217-276.

Hommes, C. (2011): The heterogeneous expectations hypothesis: Some evidence from the lab. Journal of Economic Dynamics and Control, 35, 1-24.

Huang,W., Zheng, H. and Chia, W.M. (2010): Financial crisis and interacting heterogeneous agents. Journal of Economic Dynamics and Control, 34, 1105-1122.

Huang, W. and Chen, Z. (2013): Modelling propagation of financial crises. Working Paper, Nanyang Technological University Singapore.

Karolyi, A. and Stulz, R. (1996): Why do markets move together? An investigation of U.S.-Japan stock return comovements. The Journal of Finance, 51, 951-986.

Karolyi, A. and Stulz, R. (2003): Are financial assets priced locally or globally? In: Constantinides, G., Harris, M. and Stulz, R. (eds.): Handbook of the Economics of Finance. Elsevier, Amsterdam, 975-1020.

Karpoff, J. (1987): The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis, 22, 109-126.

Kindleberger, C. (2000): Manias, panics and crashes: A history of financial crises. Wiley, New York.

Kirman, A., Ricciotti, R and Topol, R. (2007): Bubbles in the foreign exchange market: it takes two to tango. Macroeconomic Dynamics, 11, 102-123.

Lee, B. and Rui, O. (2002): The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. Journal of Banking and Finance, 26, 51-78.

Lewis, K. (1999): Trying to explain home bias in equities and consumption. Journal of Economic Literature, 37, 571-608.

Lo, A. and Wang, J. (2010): Trading volume: Definitions, data analysis, and implications of portfolio theory. The Review of Financial Studies, 13, 257-300.

Lobato, I. and Velasco, C. (2000): Long memory in stock-market trading volume. Journal of Business and Economic Statistics, 18, 410-427.

Lux, T. (1995): Herd behaviour, bubbles and crashes. Economic Journal, 105, 881-896.

Lux, T. (2009): Stochastic behavioural asset-pricing models and the stylized facts. In: Hens, T. and Schenk-Hoppé, K.R. (eds.): Handbook of Financial Markets: Dynamics and Evolution. North-Holland, Amsterdam, 161-216.

Lux, T. and Marchesi, M. (1999): Scaling and criticality in a stochastic multi-agent model of a financial market. Nature 397, 498-500.

Lux, T. and Ausloos, M. (2002): Market fluctuations I: Scaling, multiscaling, and their possible origins. In: Bunde, A., Kropp, J. and Schellnhuber, H. (eds.): Science of disaster: climate disruptions, heart attacks, and market crashes. Springer: Berlin, 373-410.

Lux, T. and Kaizoji, T. (2007): Forecasting volatility and volume in the Tokyo stock market: Long memory, fractality and regime switching. Journal of Economic Dynamics and Control, 31, 1808-1843.

Mandelbrot, B. (1963): The variation of certain speculative prices. Journal of Business, 36, 394-419.

Mantegna, R. and Stanley, E. (2000): An Introduction to Econophysics. Cambridge University Press, Cambridge.

Manzan, S. and Westerhoff, F. (2007): Heterogeneous expectations, exchange rate dynamics and predictability. Journal of Economic Behavior and Organization 64, 111-128.

Menkhoff, L. and Taylor, M. (2007): The obstinate passion of foreign exchange professionals: technical analysis. Journal of Economic Literature, 45, 936-972.

Murphy, J. (1999): Technical analysis of financial markets. New York Institute of Finance, New York.

Pape, B. (2007): Asset allocation and multivariate position based trading. Journal of Economic Interaction and Coordination, 2, 163-193.

Podobnik, B., Fu, D., Stanley, H. and Ivanov, P. (2007): Power-law autocorrelated stochastic processes with long-range cross-correlations. The European Physical Journal B, 56, 47-52.

Shiller, R. (1981): Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review, 71, 421-436.

Shiller, R. (1989): Comovements in stock prices and comovements in dividends. Journal of Finance, 44, 719-727.

Shiller, R. (2005): Irrational exuberance. Princeton University Press, Princeton.

Sornette, D. (2003): Why stock markets crash. Princeton University Press, Princeton.

Tesar, L. and Werner, I. (1994): International equity transactions and U.S. portfolio choice. In: Frankel, J. (ed.): The internationalization of equity markets. University of Chicago Press, Chicago, 185-227.

Tramontana, F., Westerhoff, F. and Gardini, L. (2010): On the complicated price dynamics of a simple one-dimensional discontinuous financial market model with heterogeneous interacting traders. Journal of Economic Behavior and Organization, 74, 187-205.

Westerhoff, F. (2003): Speculative markets and the effectiveness of price limits. Journal of Economic Dynamics and Control, 28, 493-508.

Westerhoff, F. (2004): Multiasset market dynamics. Macroeconomic Dynamics 8, 596-616.

Westerhoff, F. and Dieci, R. (2006): The effectiveness of Keynes-Tobin transaction taxes when heterogeneous agents can trade in different markets: a behavioral finance approach. Journal of Economic Dynamics and Control, 30, 293-322.

Westerhoff, F. and Franke, R. (2013): Agent-based models for economic policy design. In: Chen, S.-H. and Kaboudan, M. (eds): OUP Handbook on Computational Economics and Finance. Oxford University Press, Oxford, in press.

Series	V	D	α	ac_r^1	ac_r^2	ac_r^3	$ac_{\|r\|}^1$	$ac_{\|r\|}^{20}$	$ac_{\|r\|}^{50}$	$ac_{\|r\|}^{100}$
DAX30	1.02	-	3.65	-0.01	-0.03	-0.02	0.22	0.19	0.14	0.11
CAC40	1.00	-	3.58	0.00	-0.03	-0.05	0.17	0.17	0.09	0.08
FTSE100	0.80	-	3.28	-0.01	-0.04	-0.06	0.23	0.17	0.12	0.10
IBEX35	0.98	-	3.70	0.04	-0.04	-0.04	0.23	0.20	0.12	0.09
S&P500	0.78	-	3.20	-0.06	-0.04	0.00	0.22	0.23	0.16	0.12
NIKKEI225	1.06	-	3.31	-0.02	-0.05	0.00	0.21	0.15	0.08	0.07

Table 1: Univariate statistical properties of international stock markets. The table contains estimates of the volatility *V*, the distortion *D*, the tail index *a*, the autocorrelation function of raw returns ac_r^i for lags $i \in \{1,2,3\}$ and the autocorrelation function of absolute returns $ac_{|r|}^i$ for lags $i \in \{1,20,50,100\}$. The time series range from January 1, 1988 to December 31, 2012 and contain between 6155 and 6321 daily observations (national holidays have been eliminated).

Series	cc_r^{-1}	cc_r^0	cc_r^{+1}	$cc_{\|r\|}^{-50}$	$cc_{\|r\|}^{-25}$	$cc_{\|r\|}^{-1}$	$cc_{\|r\|}^0$	$cc_{\|r\|}^{+1}$	$cc_{\|r\|}^{+25}$	$cc_{\|r\|}^{+50}$
DAX30/ CAC40	0.02	0.79	0.03	0.13	0.18	0.18	0.73	0.20	0.14	0.10
DAX30/ FTSE100	0.02	0.71	0.02	0.14	0.19	0.19	0.63	0.28	0.14	0.09
DAX30/ IBEX35	0.02	0.71	0.03	0.11	0.17	0.18	0.63	0.21	0.14	0.08
CAC40/ FTSE100	0.00	0.80	-0.02	0.11	0.17	0.19	0.72	0.21	0.14	0.11
CAC40/ IBEX35	-0.01	0.79	0.01	0.10	0.16	0.18	0.71	0.19	0.16	0.09
FTSE100/ IBEX35	-0.01	0.71	0.01	0.10	0.15	0.20	0.61	0.19	0.16	0.11

Table 2: Bivariate statistical properties of international stock markets. The table contains estimates of the cross-correlation function of raw returns cc_r^i for lags $i \in \{-1,0,1\}$ and the cross-correlation function of absolute returns $cc_{|r|}^i$ for lags $i \in \{-50,-25,-1,0,1,25,50\}$. The time series range from January 1, 1988 to December 31, 2012 and consist of 6522 daily observations (to preserve synchronicity, national holidays have not been eliminated).

Mean/ Quantile	V	D	α	ac_r^1	ac_r^2	ac_r^3	$ac_{\|r\|}^1$	$ac_{\|r\|}^{20}$	$ac_{\|r\|}^{50}$	$ac_{\|r\|}^{100}$
Mean	0.83	26.62	3.30	0.01	0.00	0.00	0.25	0.19	0.14	0.10
0.05	0.68	21.97	2.87	-0.02	-0.03	-0.03	0.19	0.13	0.09	0.04
0.25	0.76	24.79	3.11	0.00	-0.01	-0.01	0.22	0.17	0.12	0.07
0.50	0.83	26.66	3.29	0.01	0.00	0.00	0.25	0.19	0.14	0.09
0.75	0.88	28.49	3.48	0.02	0.01	0.01	0.27	0.21	0.16	0.12
0.95	0.98	31.21	3.78	0.04	0.03	0.03	0.31	0.25	0.20	0.15

Table 3: Univariate statistical properties of our model. The table contains estimates of means and quantiles of the volatility *V*, the distortion *D*, the tail index *a*, the autocorrelation function of raw returns ac_r^i for lags $i \in \{1,2,3\}$ and the autocorrelation function of absolute returns $ac_{|r|}^i$ for lags $i \in \{1,20,50,100\}$. Computations are based on 5000 time series, each containing 6500 observations.

Mean/ Quantile	cc_r^{-1}	cc_r^0	cc_r^{+1}	$cc_{\|r\|}^{-50}$	$cc_{\|r\|}^{-25}$	$cc_{\|r\|}^{-1}$	$cc_{\|r\|}^0$	$cc_{\|r\|}^{+1}$	$cc_{\|r\|}^{+25}$	$cc_{\|r\|}^{+50}$
Mean	0.01	0.80	0.01	0.12	0.13	0.13	0.65	0.13	0.13	0.12
0.05	-0.02	0.75	-0.02	0.06	0.07	0.06	0.56	0.06	0.07	0.06
0.25	0.00	0.78	0.00	0.09	0.11	0.11	0.61	0.11	0.11	0.09
0.50	0.01	0.80	0.01	0.12	0.13	0.14	0.65	0.14	0.13	0.12
0.75	0.02	0.82	0.02	0.14	0.16	0.16	0.69	0.16	0.16	0.14
0.95	0.03	0.85	0.03	0.17	0.19	0.20	0.74	0.20	0.19	0.17

Table 4: Bivariate statistical properties of our model. The table contains estimates of means and quantiles of the cross-correlation function of raw returns cc_r^i for lags $i \in \{-1,0,1\}$ and the cross-correlation function of absolute returns $cc_{|r|}^i$ for lags $i \in \{-50,-25,-1,0,1,25,50\}$. Computations are based on 5000 time series, each containing 6500 observations.

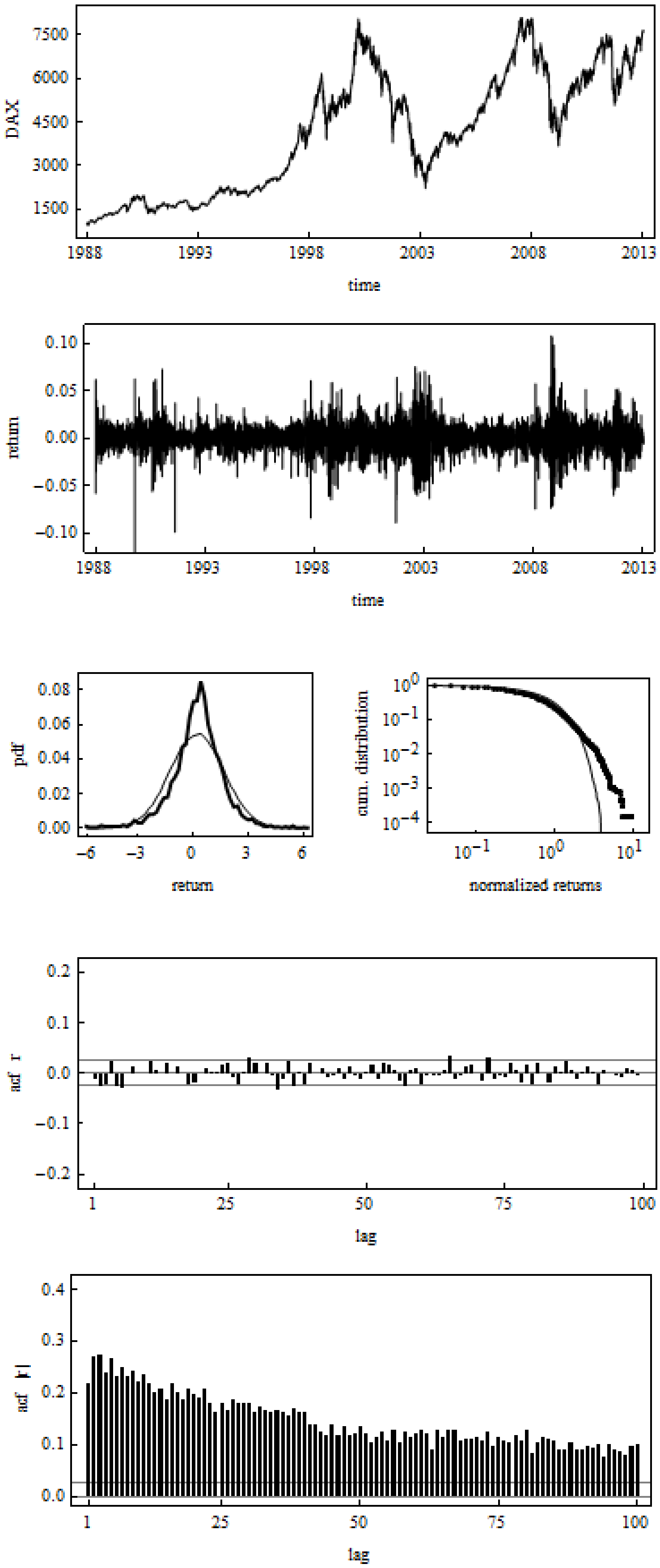


Figure 1: The dynamics of the DAX30 between 1988 and 2012. The panels show from top to bottom the evolution of the DAX30, the returns, the distribution of returns, the cumulative distribution of normalized returns and the autocorrelation functions of raw and absolute returns, respectively.

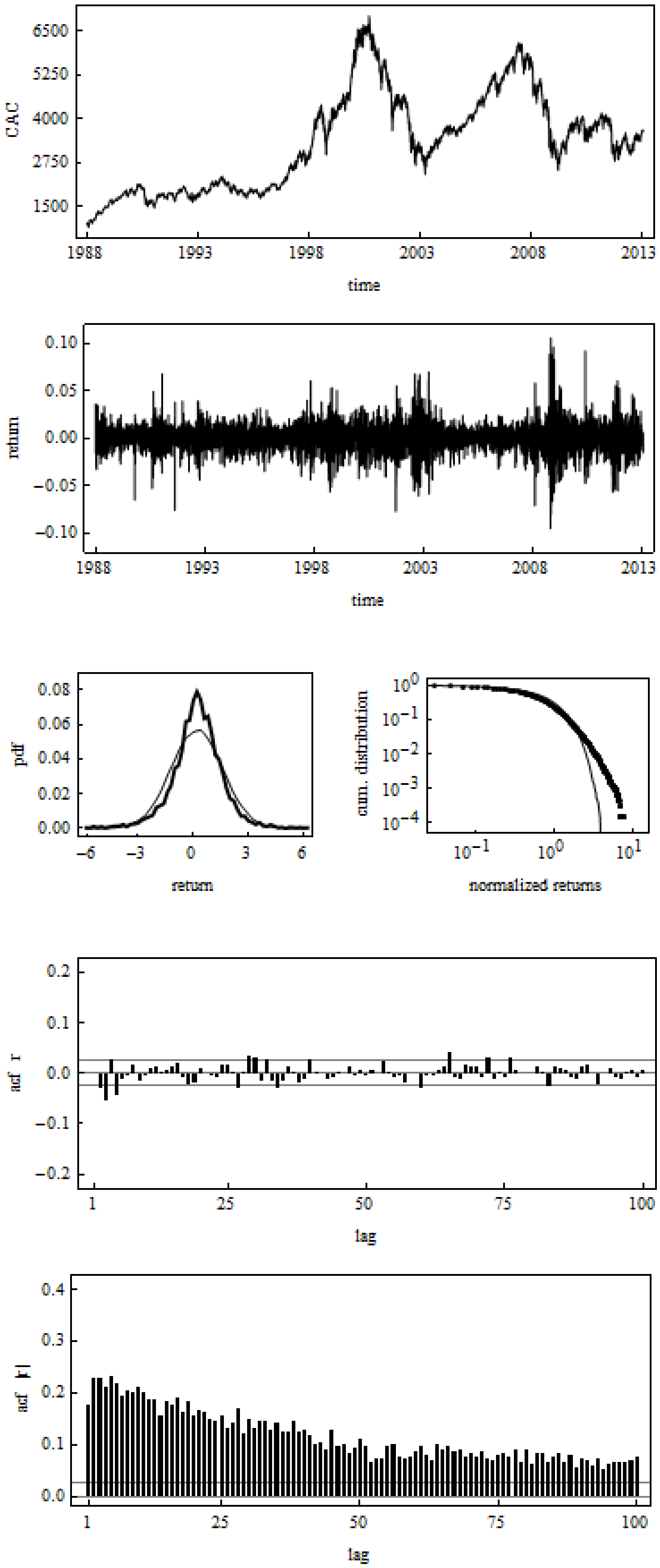


Figure 2: The dynamics of the CAC40 between 1988 and 2012. The panels show from top to bottom the evolution of the CAC40, the returns, the distribution of returns, the cumulative distribution of normalized returns and the autocorrelation functions of raw and absolute returns, respectively.

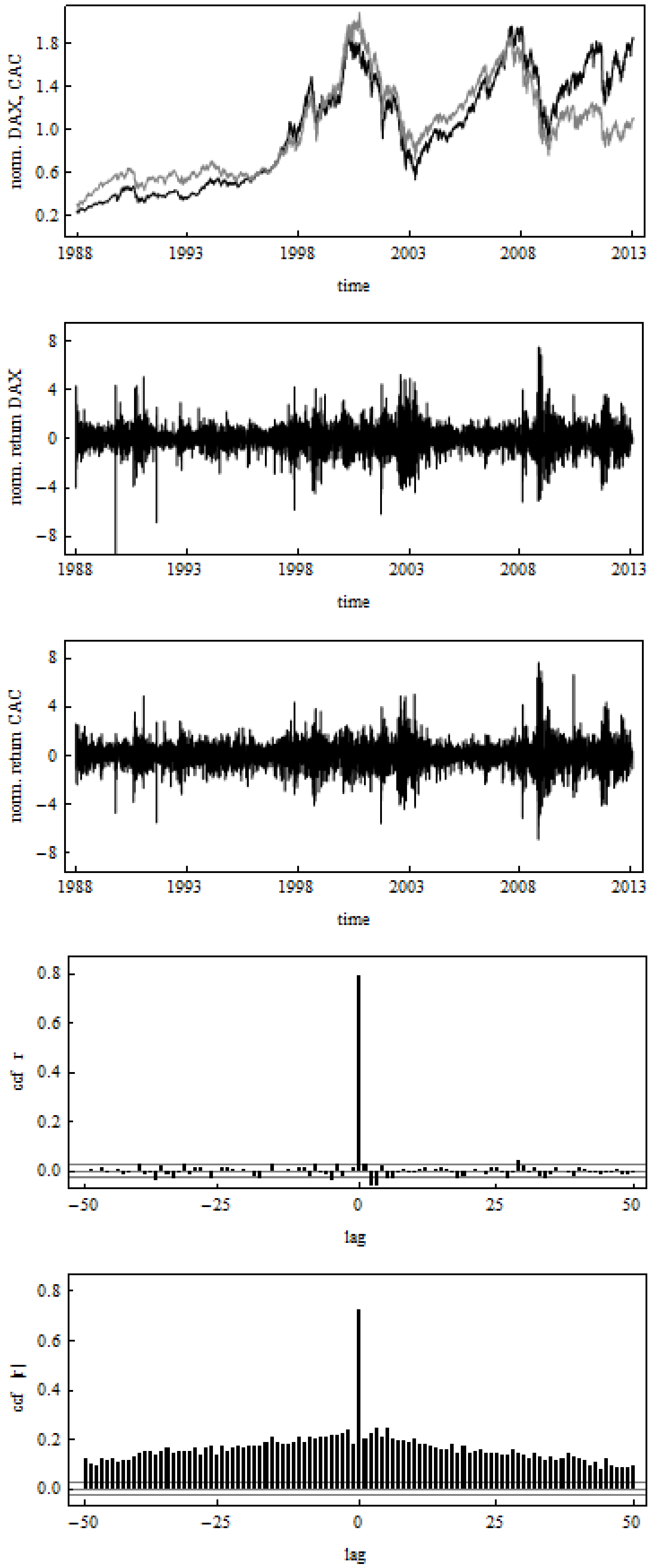


Figure 3: Dynamic relations between the DAX30 and the CAC40 between 1988 and 2012. The panels show from top to bottom the evolution of the normalized DAX30 (black) and the normalized CAC40 (gray), their normalized returns and the cross-correlation functions of raw and absolute returns, respectively.

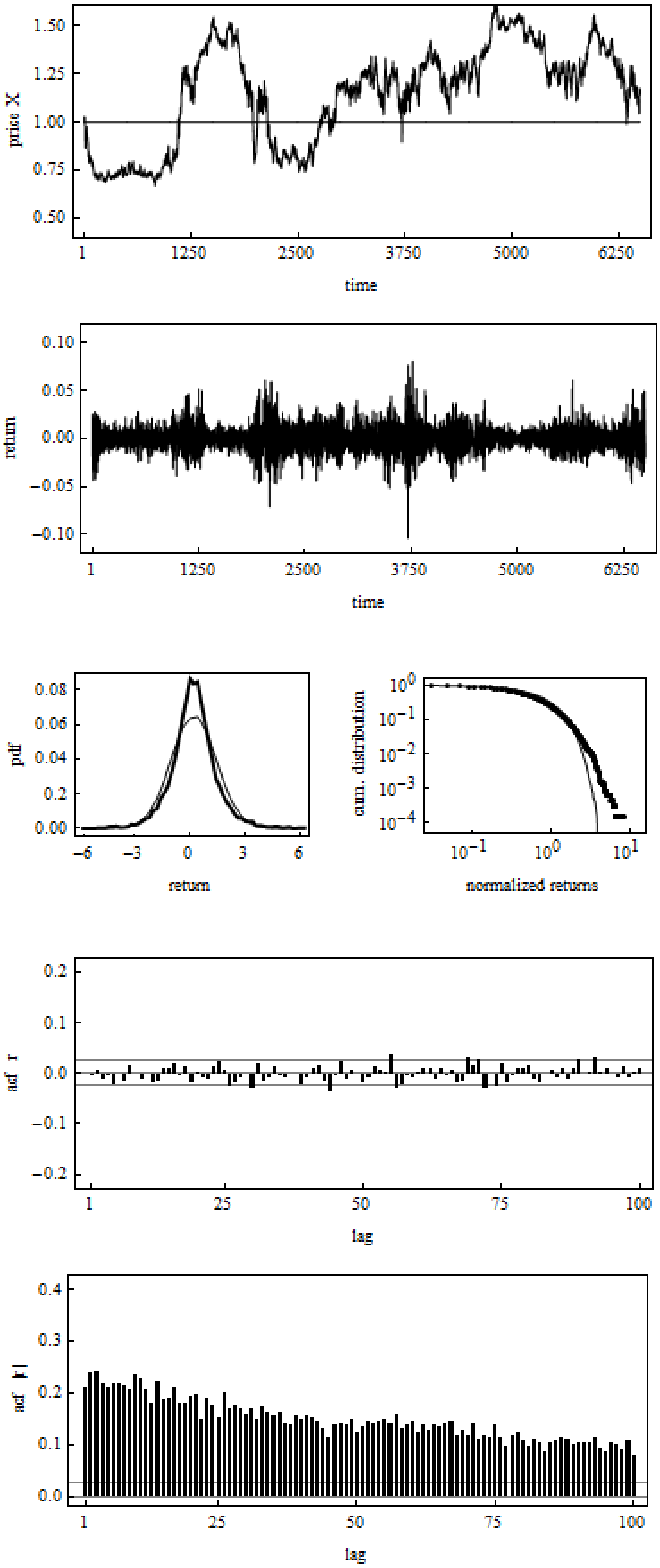


Figure 4: The dynamics of stock market X. The panels show from top to bottom the evolution of stock prices in market X, the returns, the distribution of returns, the cumulative distribution of normalized returns and the autocorrelation functions of raw and absolute returns, respectively.

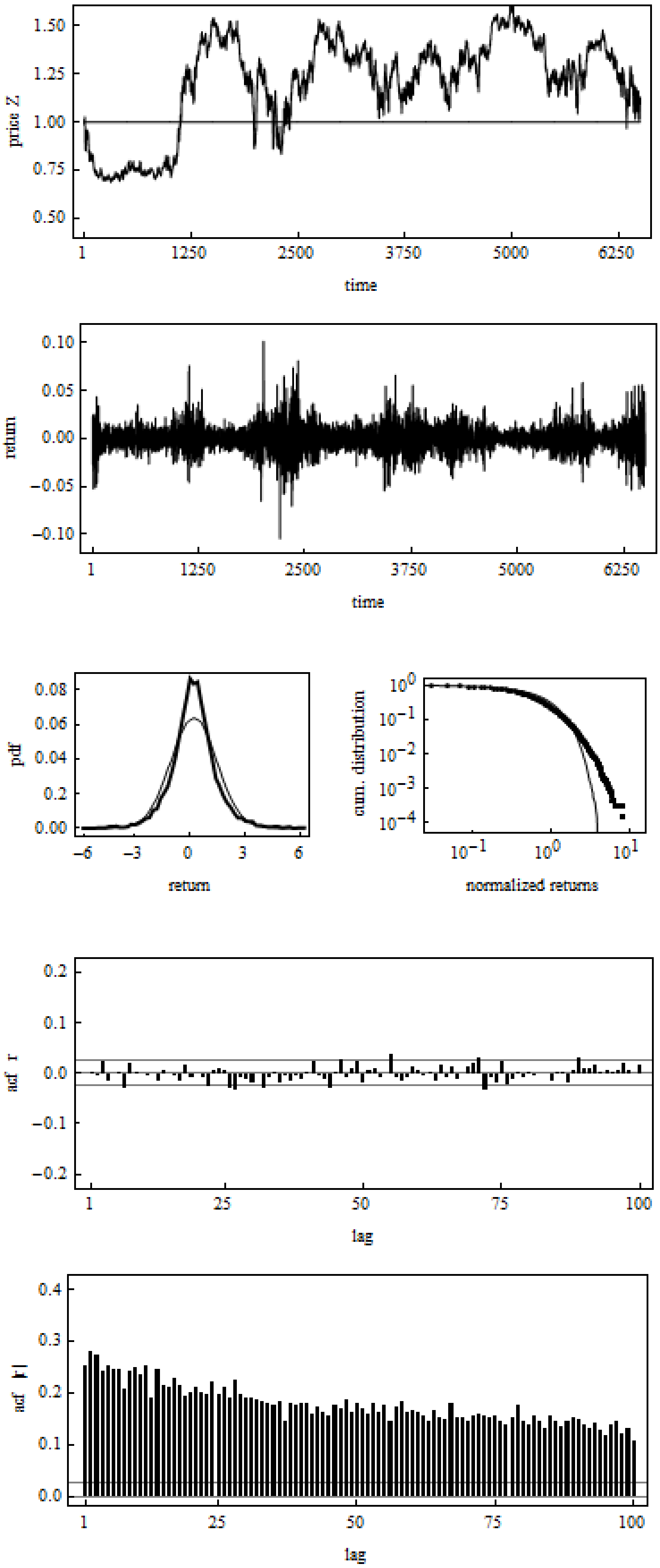


Figure 5: The dynamics of stock market Z. The panels show from top to bottom the evolution of stock prices in market Z, the returns, the distribution of returns, the cumulative distribution of normalized returns and the autocorrelation functions of raw and absolute returns, respectively.

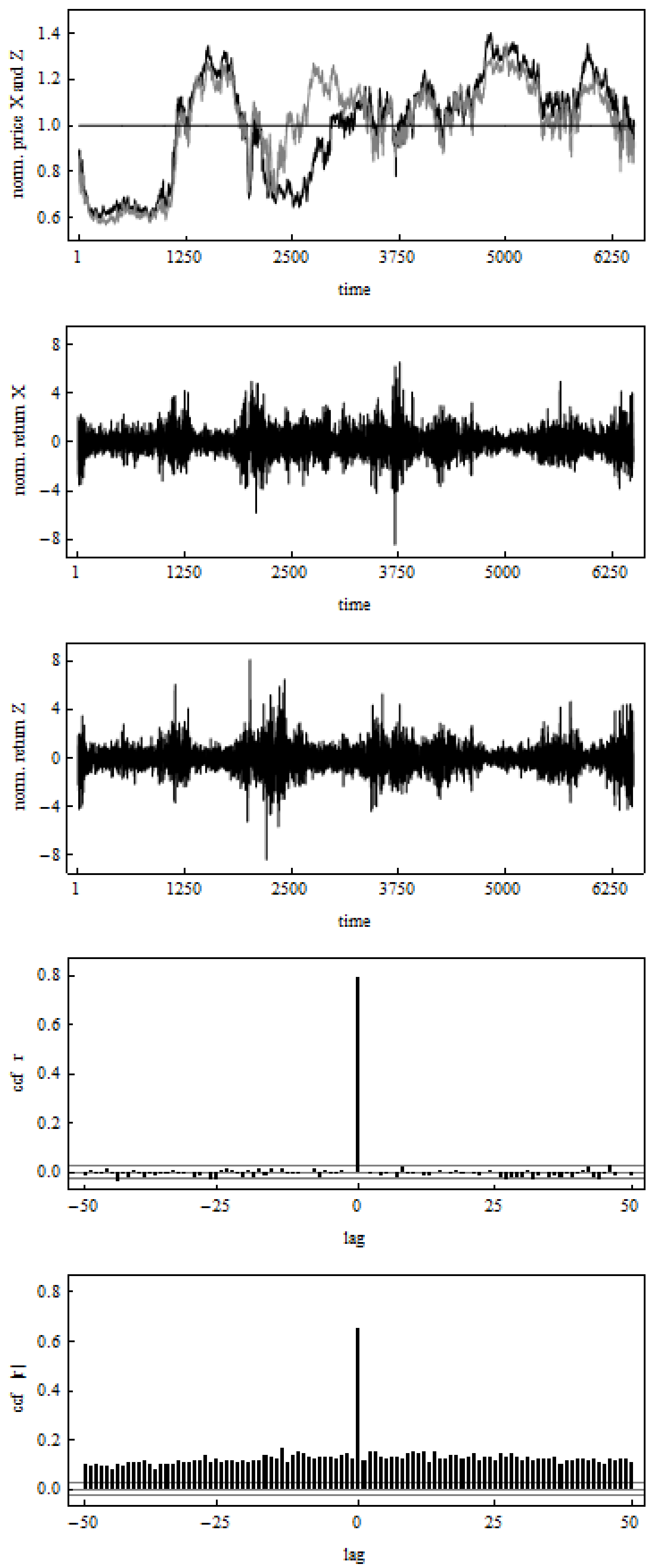


Figure 6: Dynamic relations between stock markets X and Z. The panels show from top to bottom the evolution of stock prices in markets X and Z, their normalized returns and the cross-correlation functions of raw and absolute returns, respectively.

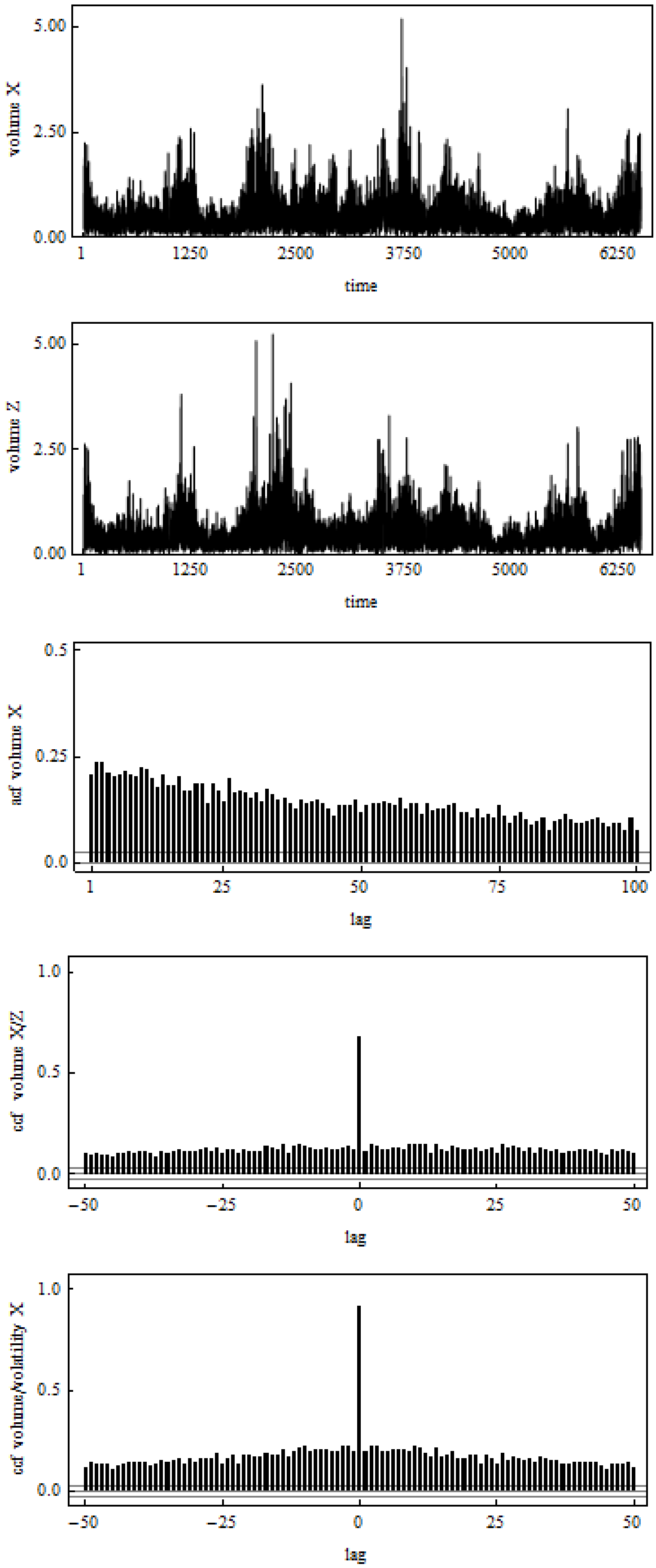


Figure 7: Properties of trading volumes and their relations to volatilities. The panels show from top to bottom the evolution of trading volumes in markets X and Z, the autocorrelation function of trading volumes in market X, the cross-correlation function of trading volumes and the cross-correlation function of trading volume and volatility on market X , respectively.

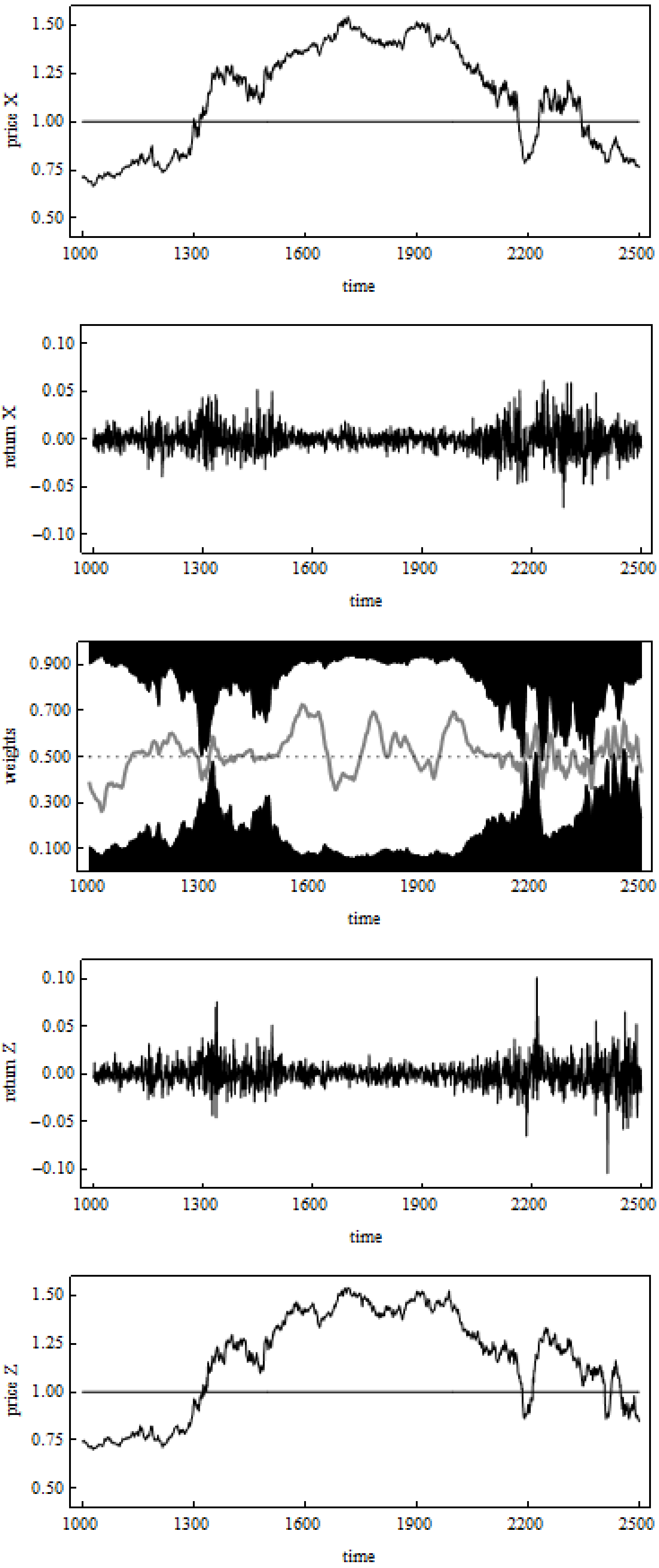


Figure 8: A snapshop of the model dynamics. The panels show from top to bottom the evolution of stock prices in market X, the returns in market X, the (stacked) market shares of chartists in market X, fundamentalists in market X, fundamentalists in market Z and chartists in market Z, the returns in market Z and stock prices in market Z from period 1000 to period 2500.

BERG Working Paper Series

1 Mikko **Puhakka** and Jennifer P. **Wissink**, Multiple Equilibria and Coordination Failure in Cournot Competition, December 1993

2 Matthias **Wrede**, Steuerhinterziehung und endogenes Wachstum, December 1993

3 Mikko **Puhakka**, Borrowing Constraints and the Limits of Fiscal Policies, May 1994

4 Gerhard **Illing**, Indexierung der Staatsschuld und die Glaubwürdigkeit der Zentralbank in einer Währungsunion, June 1994

5 Bernd **Hayo**, Testing Wagner`s Law for Germany from 1960 to 1993, July 1994

6 Peter **Meister** and Heinz-Dieter **Wenzel**, Budgetfinanzierung in einem föderalen System, October 1994

7 Bernd **Hayo** and Matthias **Wrede**, Fiscal Policy in a Keynesian Model of a Closed Monetary Union, October 1994

8 Michael **Betten**, Heinz-Dieter **Wenzel**, and Matthias **Wrede**, Why Income Taxation Need Not Harm Growth, October 1994

9 Heinz-Dieter **Wenzel** (Editor), Problems and Perspectives of the Transformation Process in Eastern Europe, August 1995

10 Gerhard **Illing**, Arbeitslosigkeit aus Sicht der neuen Keynesianischen Makroökonomie, September 1995

11 Matthias **Wrede**, Vertical and horizontal tax competition: Will uncoordinated Leviathans end up on the wrong side of the Laffer curve? December 1995

12 Heinz-Dieter **Wenzel** and Bernd **Hayo**, Are the fiscal Flows of the European Union Budget explainable by Distributional Criteria? June 1996

13 Natascha **Kuhn**, Finanzausgleich in Estland: Analyse der bestehenden Struktur und Überlegungen für eine Reform, June 1996

14 Heinz-Dieter **Wenzel**, Wirtschaftliche Entwicklungsperspektiven Turkmenistans, July 1996

15 Matthias **Wrede,** Öffentliche Verschuldung in einem föderalen Staat; Stabilität, vertikale Zuweisungen und Verschuldungsgrenzen, August 1996

16 Matthias **Wrede**, Shared Tax Sources and Public Expenditures, December 1996

17 Heinz-Dieter **Wenzel** and Bernd **Hayo**, Budget and Financial Planning in Germany, February 1997

18 Heinz-Dieter **Wenzel**, Turkmenistan: Die ökonomische Situation und Perspektiven wirtschaftlicher Entwicklung, February 1997

19 Michael **Nusser**, Lohnstückkosten und internationale Wettbewerbsfähigkeit: Eine kritische Würdigung, April 1997

20 Matthias **Wrede**, The Competition and Federalism - The Underprovision of Local Public Goods, September 1997

21 Matthias **Wrede**, Spillovers, Tax Competition, and Tax Earmarking, September 1997

22 Manfred **Dauses**, Arsène **Verny**, Jiri **Zemánek,** Allgemeine Methodik der Rechtsangleichung an das EU-Recht am Beispiel der Tschechischen Republik, September 1997

23 Niklas **Oldiges**, Lohnt sich der Blick über den Atlantik? Neue Perspektiven für die aktuelle Reformdiskussion an deutschen Hochschulen, February 1998

24 Matthias **Wrede**, Global Environmental Problems and Actions Taken by Coalitions, May 1998

25 Alfred **Maußner**, Außengeld in berechenbaren Konjunkturmodellen – Modellstrukturen und numerische Eigenschaften, June 1998

26 Michael **Nusser**, The Implications of Innovations and Wage Structure Rigidity on Economic Growth and Unemployment: A Schumpetrian Approach to Endogenous Growth Theory, October 1998

27 Matthias **Wrede**, Pareto Efficiency of the Pay-as-you-go Pension System in a Three-Period-OLG Modell, December 1998

28 Michael **Nusser**, The Implications of Wage Structure Rigidity on Human Capital Accumulation, Economic Growth and Unemployment: A Schumpeterian Approach to Endogenous Growth Theory, March 1999

29 Volker **Treier**, Unemployment in Reforming Countries: Causes, Fiscal Impacts and the Success of Transformation, July 1999

30 Matthias **Wrede**, A Note on Reliefs for Traveling Expenses to Work, July 1999

31 Andreas **Billmeier**, The Early Years of Inflation Targeting – Review and Outlook –, August 1999

32 Jana **Kremer**, Arbeitslosigkeit und Steuerpolitik, August 1999

33 Matthias **Wrede**, Mobility and Reliefs for Traveling Expenses to Work, September 1999

34 Heinz-Dieter **Wenzel (**Herausgeber**)**, Aktuelle Fragen der Finanzwissenschaft, February 2000

35 Michael **Betten**, Household Size and Household Utility in Intertemporal Choice, April 2000

36 Volker **Treier**, Steuerwettbewerb in Mittel- und Osteuropa: Eine Einschätzung anhand der Messung effektiver Grenzsteuersätze, April 2001

37 Jörg **Lackenbauer** und Heinz-Dieter **Wenzel**, Zum Stand von Transformations- und EU-Beitrittsprozess in Mittel- und Osteuropa – eine komparative Analyse, May 2001

38 Bernd **Hayo** und Matthias **Wrede**, Fiscal Equalisation: Principles and an Application to the European Union, December 2001

39 Irena Dh. **Bogdani**, Public Expenditure Planning in Albania, August 2002

40 Tineke **Haensgen**, Das Kyoto Protokoll: Eine ökonomische Analyse unter besonderer Berücksichtigung der flexiblen Mechanismen, August 2002

41 Arben **Malaj** and Fatmir **Mema**, Strategic Privatisation, its Achievements and Challenges, Januar 2003

42 Borbála **Szüle** 2003, Inside financial conglomerates, Effects in the Hungarian pension fund market, January 2003

43 Heinz-Dieter **Wenzel** und Stefan **Hopp** (Herausgeber), Seminar Volume of the Second European Doctoral Seminar (EDS), February 2003

44 Nicolas Henrik **Schwarze**, Ein Modell für Finanzkrisen bei Moral Hazard und Überinvestition, April 2003

45 Holger **Kächelein**, Fiscal Competition on the Local Level – May commuting be a source of fiscal crises?, April 2003

46 Sibylle **Wagener**, Fiskalischer Föderalismus – Theoretische Grundlagen und Studie Ungarns, August 2003

47 Stefan **Hopp**, J.-B. Say’s 1803 *Treatise* and the Coordination of Economic Activity, July 2004

48 Julia **Bersch**, AK-Modell mit Staatsverschuldung und fixer Defizitquote, July 2004

49 Elke **Thiel**, European Integration of Albania: Economic Aspects, November 2004

50 Heinz-Dieter **Wenzel**, Jörg **Lackenbauer**, and Klaus J. **Brösamle,** Public Debt and the Future of the EU's Stability and Growth Pact, December 2004

51 Holger **Kächelein**, Capital Tax Competition and Partial Cooperation: Welfare Enhancing or not? December 2004

52 Kurt A. **Hafner**, Agglomeration, Migration and Tax Competition, January 2005

53 Felix **Stübben**, Jörg **Lackenbauer** und Heinz-Dieter **Wenzel**, Eine Dekade wirtschaftlicher Transformation in den Westbalkanstaaten: Ein Überblick, November 2005

54 Arben **Malaj,** Fatmir **Mema** and Sybi **Hida,** Albania, Financial Management in the Education System: Higher Education, December 2005

55 Osmat **Azzam**, Sotiraq **Dhamo** and Tonin **Kola,** Introducing National Health Accounts in Albania, December 2005

56 Michael **Teig,** Fiskalische Transparenz und ökonomische Entwicklung: Der Fall Bosnien-Hercegovina, März 2006

57 Heinz-Dieter **Wenzel** (Herausgeber), Der Kaspische Raum: Ausgewählte Themen zu Politik und Wirtschaft, Juli 2007

58 Tonin **Kola** and Elida **Liko**, An Empirical Assessment of Alternative Exchange Rate Regimes in Medium Term in Albania, Januar 2008

59 Felix **Stübben**, Europäische Energieversorgung: Status quo und Perspektiven, Juni 2008

60 Holger **Kächelein,** Drini **Imami** and Endrit **Lami**, A new view into Political Business Cycles: Household Expenditures in Albania, July 2008

61 Frank **Westerhoff**, A simple agent-based financial market model: direct interactions and comparisons of trading profits, January 2009

62 Roberto **Dieci** and Frank **Westerhoff**, A simple model of a speculative housing market, February 2009

63 Carsten **Eckel**, International Trade and Retailing, April 2009

64 Björn-Christopher **Witte**, Temporal information gaps and market efficiency: a dynamic behavioral analysis, April 2009

65 Patrícia **Miklós-Somogyi** and László **Balogh**, The relationship between public balance and inflation in Europe (1999-2007), June 2009

66 H.-Dieter **Wenzel** und Jürgen **Jilke**, Der Europäische Gerichtshof EuGH als Bremsklotz einer effizienten und koordinierten Unternehmensbesteuerung in Europa?, November 2009

67 György **Jenei**, A Post-accession Crisis? Political Developments and Public Sector Modernization in Hungary, December 2009

68 Marji **Lines** and Frank **Westerhoff**, Effects of inflation expectations on macroeconomic dynamics: extrapolative versus regressive expectations, December 2009

69 Stevan **Gaber**, Economic Implications from Deficit Finance, January 2010

70 Abdulmenaf **Bexheti,** Anti-Crisis Measures in the Republic of Macedonia and their Effects – Are they Sufficient?, March 2010

71 Holger **Kächelein**, Endrit **Lami** and Drini **Imami,** Elections Related Cycles in Publicly Supplied Goods in Albania, April 2010

72 Annamaria **Pfeffer**, Staatliche Zinssubvention und Auslandsverschuldung: Eine Mittelwert-Varianz-Analyse am Beispiel Ungarn, April 2010

73 Arjan **Tushaj**, Market concentration in the banking sector: Evidence from Albania, April 2010

74 Pál **Gervai**, László **Trautmann** and Attila **Wieszt**, The mission and culture of the corporation, October 2010

75 Simone **Alfarano** and Mishael **Milaković**, Identification of Interaction Effects in Survey Expectations: A Cautionary Note, October 2010

76 Johannes **Kalusche**, Die Auswirkungen der Steuer- und Sozialreformen der Jahre 1999-2005 auf die automatischen Stabilisatoren Deutschlands, October 2010

77 Drini **Imami,** Endrit **Lami** and Holger **Kächelein,** Political cycles in income from privatization – The case of Albania, January 2011

78 Reiner **Franke** and Frank **Westerhoff,** Structural Stochastic Volatility in Asset Pricing Dynamics: Estimation and Model Contest, April 2011

79 Roberto **Dieci** and Frank **Westerhoff**, On the inherent instability of international financial markets: natural nonlinear interactions between stock and foreign exchange markets, April 2011

80 Christian **Aßmann**, Assessing the Effect of Current Account and Currency Crises on Economic Growth, May 2011

81 Björn-Christopher **Witte**, Fund Managers – Why the Best Might be the Worst: On the Evolutionary Vigor of Risk-Seeking Behavior, July 2011

82 Björn-Christopher **Witte**, Removing systematic patterns in returns in a financial market model by artificially intelligent traders, October 2011

83 Reiner **Franke** and Frank **Westerhoff**, Why a Simple Herding Model May Generate the Stylized Facts of Daily Returns: Explanation and Estimation, December 2011

84 Frank **Westerhoff**, Interactions between the real economy and the stock market, December 2011

85 Christoph **Wunder** and Guido **Heineck**, Working time preferences, hours mismatch and well-being of couples: Are there spillovers?, October 2012

86 Manfred **Antoni** and Guido **Heineck**, Do literacy and numeracy pay off? On the relationship between basic skills and earnings, October 2012

87 János **Seregi**, Zsuzsanna **Lelovics** and László **Balogh**, The social welfare function of forests in the light of the theory of public goods, October 2012

88 Frank **Westerhoff** and Reiner **Franke**, Agent-based models for economic policy design: two illustrative examples, November 2012

89 Fabio **Tramontana**, Frank **Westerhoff** and Laura **Gardini**, The bull and bear market model of Huang and Day: Some extensions and new results, November 2012

90 Noemi **Schmitt** and Frank **Westerhoff,** Speculative behavior and the dynamics of interacting stock markets, November 2013