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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/

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Redaktion:
Dr. Felix Stübben*

* felix.stuebben@uni-bamberg.de

Herding behavior and volatility clustering in financial markets

Noemi Schmitt and Frank Westerhoff*

University of Bamberg, Department of Economics,
Feldkirchenstrasse 21, 96045 Bamberg, Germany

Abstract

We propose a simple agent-based financial market model in which speculators follow a linear mix of technical and fundamental trading rules to determine their orders. Volatility clustering arises in our model due to speculators' herding behavior. In case of heightened uncertainty, speculators observe other speculators' actions more closely. Since speculators' trading behavior then becomes less heterogeneous, the market maker faces a less balanced excess demand and consequently adjusts prices more strongly. Estimating our model using the method of simulated moments reveals that it is able to explain a number of stylized facts of financial markets quite well.

Keywords: Agent-based financial market models, stylized facts of financial markets, technical and fundamental analysis, heterogeneity, herding behavior, method of simulated moments

JEL classification: C63, D84, G15

1. Introduction

Our goal is to develop a simple agent-based model to explain a number of important stylized facts of financial markets. In particular, we seek to show that a temporal herding-induced coordination of speculators' trading behavior can lead to a high volatility period. In a nutshell, the key insight offered by our model may be summarized as follows. Speculators usually follow a diverse set of technical and fundamental trading rules to determine their orders. As a result, their buying and selling orders are roughly balanced and the market maker only has to deal with a relatively modest excess demand. However, speculators are subject to herding behavior. In periods of heightened uncertainty, speculators observe other speculators' actions more

*Corresponding author's email address: frank.westerhoff@uni-bamberg.de

closely. Copying the behavior of others implies a decrease in heterogeneity among speculators. Since more speculators are then located on either the buy side or the sell side of the market, the market maker faces a less balanced excess demand and therefore adjusts prices more strongly. We estimate our model using the method of simulated moments. Overall, we find that our model is able to produce bubbles and crashes, excess volatility, fat-tailed return distributions, uncorrelated returns and volatility clustering.

Since herding behavior plays a crucial role in our approach, let us continue by reviewing related work from this research domain. Baddeley (2010) defines herding behavior as the phenomenon of individuals deciding to follow others and imitating group behavior rather than deciding independently and atomistically on the basis of their own private information. Even Keynes stressed the importance of herding behavior and argued that people tend to herd during periods of heightened uncertainty since they are afraid of making mistakes in isolation. For instance, a famous quote by Keynes (1936, p. 158) is that: "Worldly wisdom teaches that it is better to fail conventionally than to succeed unconventionally". Keynes' view on herding behavior inspired a number of theoretical, experimental and empirical studies. For instance, Scharfstein and Stein (1990) theoretically demonstrate that it might be rational for agents to herd if they are concerned about their reputation. Moreover, Palley (1995) develops a model in which herding occurs if agents are risk averse and if their rewards depend on their relative performance. During periods of uncertainty, agents then seek what he calls "safety in numbers". Another prominent study revealing that uncertainty may promote rational herding behavior is by Avery and Zemsky (1998).

Cipriani and Guarino (2009, 2014) confirm experimentally and empirically that rational herding behavior may increase due to uncertainty. Conducting a survey study to explore the reasons for the US stock market crash of October 1987, Shiller (1990, p. 58) concludes - with a much stronger behavioral emphasis - that "The suggestion we get of the causes of the crash is one of people reacting to each other with heightened attention and emotion, trying to fathom what other investors were likely to do, and falling back on intuitive models like models of price reversal and continuation". Similarly, Shiller and Pond (1989) find that herding behavior increases not only in periods of crises but also when prices rise quickly. It seems that institutional and individual investors are more likely to be subject to contagion effects if they experience stress. In addition, Hommes et al. (2005) and Heemeijer et al. (2009) conduct learning-to-forecast experiments and report that subjects tend to coordinate on common prediction strategies. Subjects' coordination behavior is particularly strong in positive feedback systems such as financial markets. Chiang and Zheng (2010) detect strong evidence of herding behavior in global stock markets. They claim that herding behavior is present in up and down markets and, most importantly for our approach, that it is stronger in turbulent periods than in calm ones. Further psychological evidence provided by Prechter and Parker (2007) and Baddeley (2010) reveals that, under conditions of certainty, people tend to reason consciously, but tend to herd unconsciously under conditions of uncertainty.

Backed by these insights, we assume in our model that speculators' herding behavior increases with uncertainty. Moreover, we capture uncertainty via a smoothed measure of the market's past volatility. To be precise, we consider a stock market which is populated by a market maker and a fixed number of heterogeneous speculators. The market maker mediates transactions out of equilibrium and adjusts the stock price with respect to speculators' excess demand. Speculators use a linear mix of technical and fundamental trading rules to determine their orders. To capture the diversity of actual trading rules, we add random variables to speculators' demand functions. These random variables are multivariate normal distributed with a mean vector of zeros and a time-varying variance-covariance matrix. We assume that the correlation between the random parts of speculators' trading signals increases with the market's past volatility. Economically, this means that speculators follow more closely what others do in periods of heightened uncertainty. Note that this kind of herding behavior, which is in line with the aforementioned empirical and experimental literature, influences the heterogeneity of applied trading rules and thereby the market's price dynamics.

Fortunately, our approach allows a convenient aggregation of speculators' trading behavior and, as it turns out, its dynamics depends on three equations only. Simulations reveal that our simple agent-based model is able to match several salient statistical properties of financial markets. The functioning of our agent-based model may be understood as follows. Simply speaking, there are two coexisting regimes - a calm regime and a turbulent regime. In the calm regime, i.e. in periods when volatility is rather low, speculators act more or less independently. Since large parts of their orders cancel out, the market maker's price adjustments are rather modest, and volatility remains low. In the turbulent regime, i.e. in periods when volatility is high, speculators observe other speculators' actions more closely. This kind of herding behavior naturally implies that speculators' behavior becomes increasingly aligned. Since speculators' orders cancel out less strongly, the market maker faces a higher excess demand. As a result, the market maker's price adjustments are more pronounced and volatility remains high.

Although the calm and turbulent regimes are persistent, the model's long-run behavior is characterized by a regime-switching process. Regime changes, which give rise to volatility clustering, occur as follows. Even in a calm period, there may be a sequence of days when speculators receive strong trading signals and their increased trading intensity drives up volatility due to the market maker's price adjustments. A higher volatility can then lead to a herding-induced coordination of speculators' behavior and thus the onset of a turbulent period. Alternatively, even in a turbulent period there may be a sequence of days when speculators receive weak trading signals, causing volatility to decline. Consequently, herding-induced coordination among speculators dissolves and a calm period emerges. As we will see, our model can also explain other stylized facts. For instance, speculators' trading behavior gives rise to misalignments and excess volatility. While the technical components of speculators' trading rules can trigger bubbles, the fundamental components of their trading rules ensure that stock prices eventually revert to their fundamental values. Nevertheless, stock price changes are virtually impossible to predict, i.e. the development of stock prices appears as a random walk. The main reason for this outcome is that speculators rely on a myriad of time-varying trading rules. Moreover, extreme returns may emerge if speculators coordinate their behavior, leading to fat-tailed return distributions.

We use two different datasets of the S&P500 to estimate our model. To get an idea of the stock market's average misalignment, we compute the stock market's fundamental value as proposed by Shiller (2015) in his Nobel Prize lecture. This dataset, which runs from January 1871 to October 2015, contains 1,738 monthly observations. To capture the stock market's return dynamics, we focus on the S&P500's daily behavior between 1964 and 2014. This dataset contains 12,797 observations. Inspired by recent econometric work on the possible estimation of agent-based models using the method of simulated moments (see, e.g. Winker et al. 2007, Franke 2009, Franke and Westerhoff 2012 and Chen and Lux 2015), we define 12 summary statistics (moments) to capture five stylized facts of financial markets. To the best of our knowledge, we are the first to utilize the dataset of Shiller (2015) to match the S&P500's misalignment in such an endeavor. As in previous studies, the other 11 moments measure the volatility of the market, the fat-tailedness of the distribution of returns, the random walk behavior of stock prices and the volatility clustering phenomenon. Overall, the model's moment matching may be deemed as quite acceptable. For instance, we use a bootstrap procedure to compute the 95 percent confidence intervals of the 12 moments. Generating a large number of simulation runs reveals that, on average, about 85 percent of the simulated moments drop into the 95 percent confidence intervals of their empirical counterparts.

Other agent-based models can, of course, also explain the dynamics of financial markets (for an overview, see LeBaron 2006, Chiarella et al. 2009, Hommes and Wagener 2009 and Lux 2009). A couple of these studies are concerned explicitly with speculators' herding behavior.[1] Kirman (1991, 1993) proposes a random matching model in which two speculators are paired in each time step. Herding arises in this model since speculators may convince other speculators to follow their behavior. In Lux (1995) and Lux and Marchesi (1999), speculators' rule selection behavior is influenced by the relative popularity of the rules, among other things, and thus a rule may gain in popularity if it has many followers. In Cont and Bouchaud (2000) and Stauffer et al. (1999), speculators' herding behavior is of a local nature. In these models, speculators are situated on a lattice, but not all sites of the lattice are occupied. Speculators who form a local neighborhood, i.e. a cluster of connected occupied sites, either collectively buy or collectively sell assets. Note that in Kirman (1991, 1993) and Lux (1995) and Lux and Marchesi (1999), speculators' herding behavior influences whether they opt for a technical or a fundamental trading rule. In Cont and Bouchaud (2000) and Stauffer et al. (1999), speculators' herding behavior determines whether they are optimists or pessimists. Within our model, speculators' herding behavior leads to a coordination of their trading activities. Since speculators take into account other speculators' actions, the heterogeneity of the trading rules applied

[1] Clearly, not all agent-based financial market models contain an explicit herding component. In Day and Huang (1990), speculators rely on nonlinear trading rules. In Brock and Hommes (1998), speculators switch between technical and fundamental trading rules with respect to the rules' past performance. In de Grauwe et al. (1993), speculators' rule selection behavior depends on the market's current misalignment. In Westerhoff (2004), speculators switch between different markets. These low-dimensional nonlinear models are able to produce complex endogenous dynamics. In contrast, the artificial stock market models by LeBaron et al. (1999) and Chen and Yeh (2001) generate realistic dynamics due to the interactions of many different types of speculators.

becomes time-varying. Given the empirical and experimental evidence, especially the view of Shiller (1990), we regard our modeling approach as a worthwhile alternative description of speculator's trading behavior.

The rest of our paper is organized as follows. In Section 2, we present a simple agent-based financial market model in which speculators are subject to herding behavior. In Section 3, we briefly recap the stylized facts of financial markets and introduce a number of summary statistics to quantify them. In Section 4, we bring our model to the data and discuss its functioning in further detail. Section 5 concludes our paper and points out a number of avenues for future research.

2. Model setup

In our simple agent-based financial market model, we consider a single stock market which is populated by a market maker and N heterogeneous speculators. While the task of the market maker is to mediate speculators' transactions and to adjust the price with respect to excess demand, speculators rely on a blend of technical and fundamental trading rules to determine their orders. According to technical analysis (Murphy 1990), prices move in trends, and buying (selling) is suggested when the price increases (decreases). Fundamental analysis (Graham and Dodd 1951) presumes that stock prices revert towards their fundamental values and recommends buying (selling) when the stock is undervalued (overvalued). Note that the stock's fundamental value is constant and known by all market participants. To capture the diversity of actual technical and fundamental trading rules and their possible combinations, we add a random term to speculators' demand functions. These random variables are multivariate normal distributed with a mean vector of zeros and a time-varying variance-covariance matrix. Moreover, speculators tend to herd. Since their herding behavior increases with market uncertainty, we assume that the correlation between speculators' random trading signals depends positively on the market's past volatility. In volatile periods, speculators' trading behavior thus becomes more aligned.

Let us turn to the details of our model. The stock price is adjusted by the market maker, who collects all speculators' individual orders and changes the price with respect to the resulting excess demand. Following Day and Huang (1990), we formalize the behavior of the market maker as

$$P_{t+1} = P_t + a^m \sum_{i=1}^{N} D_t^i, \tag{1}$$

where P_t represents the log stock price at time step t, a^m is a positive price adjustment coefficient, D_t^i stands for the order placed by speculator i and N denotes the total number of speculators. Accordingly, the market maker quotes a higher (lower) stock price if the sum of the speculators' orders is positive (negative).

As in Chiarella and Iori (2002), Chiarella et al. (2009) and Pellizzari and Westerhoff (2009), we assume that speculators' demand depends on three components. Since speculators use both technical and fundamental analysis to determine their orders, their demand entails a chartist and a fundamentalist component. The third component is a random component that is supposed to capture all digressions from the first two components. Hence, the order placed by a single speculator i can be expressed as

$$D_t^i = b^i(P_t - P_{t-1}) + c^i(F - P_t)^3 + \delta_t^i, \tag{2}$$

where b^i and c^i are positive reaction parameters and F respresents the log fundamental value. While the first component implies that speculators follow the current price trend, the second shows that speculators also bet on mean reversion. Since Day and Huang (1990) argue that speculators trade increasingly aggressively as the market's mispricing increases, we use a cubic function to model speculators' fundamental demand.

The random trading signals $\delta_t = \{\delta_t^1, \delta_t^2, ..., \delta_t^N\}'$ are multivariate normal distributed with a mean vector $\boldsymbol{\mu} = (0, 0, ..., 0)'$ and a time-varying variance-covariance matrix $\boldsymbol{\Sigma}_t$, i.e. $\delta_t \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}_t)$. The variance-covariance matrix is given by

$$\boldsymbol{\Sigma}_t = \sigma^2 \begin{bmatrix} 1 & \rho_t & \cdots & \rho_t \\ \rho_t & 1 & & \vdots \\ \vdots & & \ddots & \rho_t \\ \rho_t & \cdots & \rho_t & 1 \end{bmatrix}. \tag{3}$$

Before we proceed to describe the remaining model parts, let us introduce some simplifying transformations. Note that the sum of δ_t^i is a normal distributed random variable with a mean of zero and a variance of $\sigma^2(N + N(N-1)\rho_t)$. Hence, we can write $\sum_{i=1}^N \delta_t^i = \sigma\sqrt{N + N(N-1)\rho_t}\ \epsilon_t$ with $\epsilon_t \sim \mathcal{N}(0, 1)$.[2] Accordingly, (1)-(3) can

[2] In general, the variance of the sum of correlated random variables δ_t^i is given by the sum of their covariances, i.e. $Var(\sum_{i=1}^N \delta_t^i) = \sum_{i=1}^N \sum_{j=1}^N Cov(\delta_t^i, \delta_t^j) = \sum_{i=1}^N Var(\delta_t^i) + 2\sum_{i=1}^{N-1} \sum_{j=i+1}^N Cov(\delta_t^i, \delta_t^j)$. In our case, random variables δ_t^i have equal variances $Var(\delta_t^i) = \sigma^2$ and their covariances are given by $Cov(\delta_t^i, \delta_t^j) = \rho_t\sigma^2$. Therefore, we have $Var(\sum_{i=1}^N \delta_t^i) =$

be summarized by

$$P_{t+1} = P_t + a^M\{(P_t - P_{t-1})\sum_{i=1}^{N} b^i + (F - P_t)^3 \sum_{i=1}^{N} c^i + \sigma\sqrt{N + N(N-1)\rho_t}\ \epsilon_t\}. \quad (4)$$

To make the dynamics independent of N, we set $a^M = a/N$, $\sigma = d\sqrt{N}$ and $\rho_t = \frac{X_t}{N-1}$ with $0 \leq X_t \leq N-1$. Note that such rescaling is implicitly done in all small-scale agent-based models with a continuum of speculators, e.g. in Day and Huang (1990), Lux (1995) and Brock and Hommes (1998). By defining $\frac{1}{N}\sum_{i=1}^{N} b^i = b$ and $\frac{1}{N}\sum_{i=1}^{N} c^i = c$, (4) turns into

$$P_{t+1} = P_t + a\ \{b\ (P_t - P_{t-1}) + c\ (F - P_t)^3 + d\sqrt{1 + X_t}\ \epsilon_t\}, \quad (5)$$

where $\epsilon_t \sim \mathcal{N}(0,1)$. As can be seen, the market maker's price adjustment depends on speculators' average technical and fundamental trading signal and on the correlation between their random trading signals.

Supported by the empirical and experimental literature, we assume that speculators are subject to herding behavior and that they tend to herd more strongly in periods of heightened uncertainty. We quantify uncertainty by a smoothed measure of the market's past volatility, i.e.

$$V_t = mV_{t-1} + (1-m)(P_t - P_{t-1})^2, \quad (6)$$

where $0 \leq m < 1$ is a memory parameter. For $m = 0$, speculators have no memory, and the volatility measure depends only on the most recent price movement. For increasing values of m, i.e. if speculators' memories improve, the volatility measure depends more strongly on past price movements.

To capture the greater synchronization of speculators' trading behavior in periods of great uncertainty, we assume that the correlation between their random trading signals increases with the market's past volatility. Recall that the correlation coefficient is defined as $0 \leq \rho_t = \frac{X_t}{N-1} \leq 1$. This assumption implies that the correlation increases with X_t and decreases with N. However, we model the time-varying value of X_t using a logistic function, i.e.

$$X_t = \frac{x}{1 + exp[-k(V_t - v)/v]}, \quad (7)$$

where $x > 0$ indicates the maximum value of (7), $k > 0$ describes the steepness of (7) and $v > 0$ determines at which volatility level (7) has its midpoint ($= x/2$). The

$N\sigma^2 + 2\frac{N(N-1)}{2}\rho_t\sigma^2 = \sigma^2(N + N(N-1)\rho_t)$.

S-shaped (sigmoid) curve (7) ensures that X_t, and thus speculators' coordination behavior, increases with the market's past volatility.

The dynamics of our model is driven by equations (5), (6) and (7). Since a is a scaling parameter and since our dynamics depends on neither F nor N, there remain seven parameters to be specified, namely b, c, d, k, v, x and m. To improve our understanding of the model's functioning, let us briefly explore two extreme model cases. For $k = 0$, the sigmoid function (7) becomes a straight line, i.e. $X_t = x/2$. This turns the model's law of motion into

$$P_{t+1} = P_t + a \left\{ b \ (P_t - P_{t-1}) + c \ (F - P_t)^3 + d' \ \epsilon_t \right\} \tag{8}$$

with $d' = d \ \sqrt{1 + 0.5x}$. As can be seen, (8) represents a nonlinear stochastical dynamical system. Since shocks are IID distributed, this model is unable to explain the stylized facts of financial markets.

In the other extreme case, i.e. for $k = \infty$, the logistic function takes either its minimum value or maximum value. Since $X_t = 0$ for $V_t < v$ and $X_t = x$ for $V_t \geq v$, the model dynamics is due to

$$P_{t+1} = P_t + a \left\{ b \ (P_t - P_{t-1}) + c \ (F - P_t)^3 + \begin{cases} d \ \sqrt{1+x} \ \epsilon_t & if \quad V_t \geq v \\ d \ \epsilon_t & if \quad V_t < v \end{cases} \right. . \tag{9}$$

A few comments are required. First, formulation (9) allows a neat illustration of the effects of X_t. Assume that $a = 1$, $P_t = P_{t-1} = F$, $d = 1$, $\epsilon = 0.01$ and $x = 8$. For $V_t < v$, we have $X_t = 0$. As a result, we observe a return of $r_{t+1} = P_{t+1} - P_t = \epsilon_t = 0.01$. For $V_t \geq v$, we have $X_t = 8$ and the return is given by $r_{t+1} = P_{t+1} - P_t = \sqrt{1+8}\epsilon_t = 0.03$. Hence, the market maker's price adjustment triples if the market switches from a low volatility regime in which speculators act independently to a high volatility regime in which their behavior is correlated. Second, we will see in the sequel that even a small correlation between random trading signals may suffice to obtain realistic dynamics. For instance, $x = 8$ implies for $N = 101$ a mere correlation of either $\rho_t = 0$ or $\rho_t = 0.08$. Assuming that there are 201 speculators would imply that the correlation is even lower, given either by $\rho_t = 0$ or $\rho_t = 0.04$. Third, from a mathematical point of view, model (9) is similar to that of Manzan and Westerhoff (2005). They propose a behavioral exchange rate model in which speculators' overreactions and underreactions to news depend on the market's past volatility. In a low (high) volatility regime, speculators underreact (overreact) to fundamental shocks and thus volatility remains persistently low (high). Note that this model was successfully estimated by Franke (2009). Therefore, the more flexible functional form of model (5) to (7) may be a good candidate for replicating the dynamics of financial markets. Needless to say, the economic story of Manzan and Westerhoff (2005) is quite different to ours.

3. Stylized facts and estimation strategy

The goal of our paper is to develop a simple agent-based model which is able to explain a number of important stylized facts of financial markes. In particular, we seek to show that our model produces bubbles and crashes, excess volatility, fat-tailed return distributions, uncorrelated returns and volatility clustering. We begin this section by briefly reviewing these properties. For general reviews of the statistical properties of financial markets see, for instance, Mantegna and Stanley (2000), Cont (2001) or Lux and Ausloos (2002). Our exposition of these universal features is based on two different datasets of the S&P500. The first dataset, obtained from Shiller (2015), ranges from January 1871 to October 2015 and contains 1,738 monthly observations. The second dataset, downloaded from Thomson Reuters Datastream, runs from January 1, 1964 to December 31, 2014 and contains 12,797 daily observations.

The dynamics of the S&P500 is depicted in Figure 1. In the first panel, we illustrate the evolution of the real S&P500 (black) and its real fundamental value (gray) on a log scale between 1871 and 2015. The fundamental value is computed as proposed in Shiller (2015). As can be seen, stock prices display bubbles and crashes. To visualize the S&P500's distortion more clearly, we plot the log difference between the real S&P500 and its real fundamental value in the second panel of Figure 1. Obviously, the market's distortion varies over time and there are periods with strong mispricing as well as periods when prices are less distorted.

The third panel of Figure 1 displays the daily returns of the S&P500 between 1964 and 2014 and reveals that prices fluctuate strongly. Overall, it seems that the volatility of prices is higher than warranted by fundamentals. The fat tail property of the distribution of returns is exemplified in the fourth line of Figure 1. In the left panel, the log-linear plot of the distribution of normalized returns (black) is compared with that of standard normally distributed returns (gray). Recall that returns are normalized by dividing by the standard deviation. The empirical distribution clearly possesses more probability mass in the tails and implies that extreme returns occur more frequently than suggested by a normal distribution. To quantify the fat tail

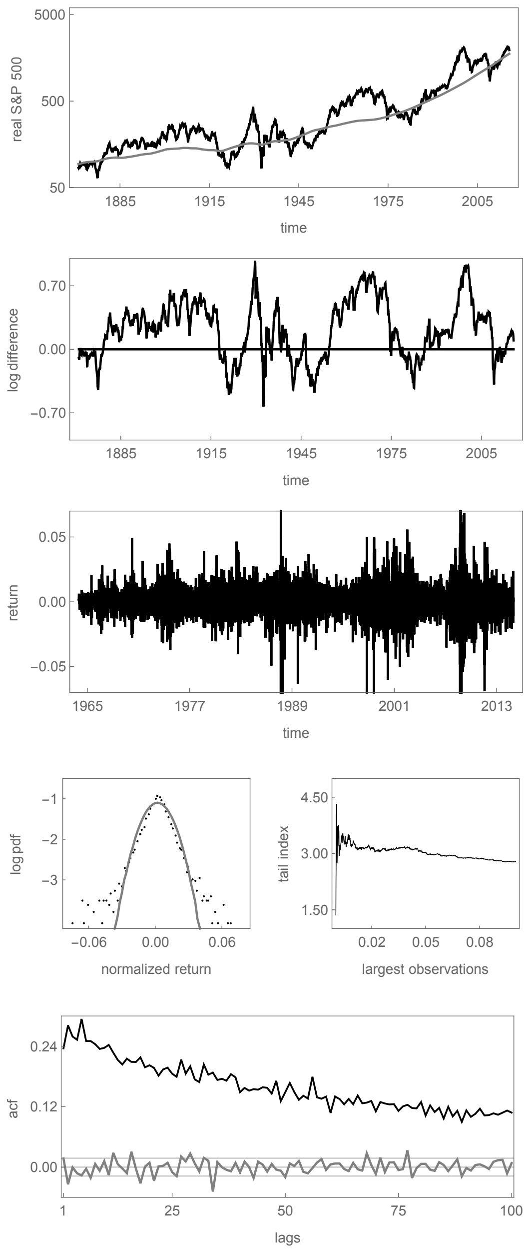

Figure 1: The dynamics of the S&P500. The first panel shows the real S&P500 (black) and its real fundamental value (gray) on a log scale between 1871 to 2015, while their respective log difference is plotted in the second panel. The remaining panels illustrate the S&P500's daily behavior between 1964 and 2014 and show the returns, the log distribution of normalized returns, the Hill tail index estimator as a function of the largest returns and the autocorrelation function of raw returns (gray) together with the autocorrelation function of absolute returns (black), respectively. The first two panels are based on a time series with 1,738 monthly observations; the other panels are based on 12,797 daily observations.

property, we estimate the Hill tail index (Hill 1975) and plot it as a function of the largest returns (in percent) in the right panel of the fourth line. For instance, computing the Hill tail index at the 5 percent level yields a value of 3.02. Note that the lower the value for the tail index, the fatter the tails. The bottom panel displays the autocorrelation functions of raw (gray) and absolute returns (black) for the first 100 lags. Since raw returns reveal autocorrelation coefficients that are insignificant for almost all lags, the evolution of prices is close to a random walk. In contrast, absolute returns show signifant autocorrelations for more than 100 lags, which is clear evidence of temporal persistence in volatility.

To estimate our model using the method of simulated moments, we follow previous studies (e.g. Franke and Westerhoff 2012) and introduce summary statistics (moments) to measure the five stylized facts we seek to match. Due to the dataset of Shiller (2015), we are fortunately able to capture the S&P500's misalignment and define the distortion D as the mean value of the absolute difference between log stock prices and log fundamentals. By computing the average value of absolute returns, the Hill tail index at the 5 percent level, the autocorrelation coefficients of raw returns for lags 1, 2 and 3 and the autocorrelation coefficients of absolute returns for lags 3, 6, 12, 25, 50 and 100, we measure the volatility, the fat tail property, the random walk behavior of stock prices and the volatility clustering phenomenon, respectively. Estimates of these twelve moments are presented in the first lines of Table 1.

Additionally, we compute a frequency distribution for each of the moments. For this purpose, we use a bootstrap approach to obtain more empirical samples. To account for the long-range dependence in the time series, we initially follow Winker et al. (2007) and choose a block bootstrap. Thus, we subdivide our first empirical time series of the S&P500 into 28 blocks of 60 monthly observations (5 years) and construct a new time series of the same size by randomly drawing (with replacement) from these 28 blocks. We compute the distortion from this bootstrapped time series and repeat it 50,000 times to obtain its distribution. Using block lengths of four and six years produces quite similar results. All other moments' distributions are calculated from the second time series comprising daily data. In order to compute distributions of the mean value of absolute returns and the tail index, we repeat the approach described above but use 51 blocks with 250 data points (1 year) each. However, for the distributions concerning the lagged autocorrelation statistics we apply another bootstrap procedure. Franke and Westerhoff (2016) argue that the long-range dependence in the return series gets interrupted every time two non-adjacent blocks are linked. This may cause the bootstrapped coefficients to show a tendency towards lower values. To avoid this join-point problem, they suggest sampling single days and the associated past data points required to compute the lagged autocorrelation. Therefore, we form new time series by 12,800 random draws with replacement of consecutive data points from the S&P500 time series and compute the moments from them. Repeating this 5,000 times yields samples that allow us to compute the moments' distributions. The median, the lower and the upper boundary of the 95% conficence intervals of these 12 bootstrapped distributions are reported in the second, third and fourth lines of Table 1, respectively. Note that in all 12 cases, the estimated moments from the original time series are very close to the computed median values, i.e. the moments' distributions are nicely centered around their respective empirical observations.

	D	V	$\alpha_{5.0}$	$ac\ r_1$	$ac\ r_2$	$ac\ r_3$
Measured	0.310	0.697	3.052	0.017	-0.034	0.000
Median	0.316	0.696	3.073	0.017	-0.033	-0.001
Lower bound	0.255	0.625	2.691	-0.022	-0.083	-0.036
Upper bound	0.385	0.776	3.615	0.056	0.010	0.035
	$ac\ \lvert r_3\rvert$	$ac\ \lvert r_6\rvert$	$ac\ \lvert r_{12}\rvert$	$ac\ \lvert r_{25}\rvert$	$ac\ \lvert r_{50}\rvert$	$ac\ \lvert r_{100}\rvert$
Measured	0.259	0.250	0.227	0.186	0.149	0.108
Median	0.259	0.249	0.227	0.185	0.149	0.109
Lower bound	0.217	0.209	0.191	0.155	0.124	0.087
Upper bound	0.309	0.296	0.268	0.218	0.177	0.132

Table 1: The empirical moments of the S&P500 and their frequency distributions. The first lines contain estimates of the distortion D, the volatility V, the tail index $\alpha_{5.0}$, 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 $i \in \{3, 6, 12, 25, 30, 100\}$. In the second, third and fourth lines, we report for all 12 moments the median, and the lower and upper boundary of the 95% confidence intervals of their bootstrapped distributions, respectively.

The basic idea of our estimation strategy is to find the parameter setting for which the model's simulated moments fall most frequently into the 95% confidence intervals of their empirical counterparts. To be more precise, we assign points to cases in which the considered moments match their empirical intervals and set up an objective function that simply adds up these points and divides the total point score by 12. The estimation then searches for the parameter setting that maximizes this average moment matching score ($= AMMS$).[3]

4. The dynamics of the model

We are now ready to bring our model to the data. In Section 4.1, we report our estimation results and discuss the performance of our model. In Section 4.2, we present a representative simulation run of our model to explain its functioning in further detail.

4.1. The performance of the model

Recall that the market maker's price adjustment parameter is a scaling parameter and that the dynamics of model (5)-(7) does not depend on the level of the log fundamental value. Without loss of generality, we thus set $a = 1$ and $F = 0$. For the remaining seven model parameters, the maximization of the average moment matching score yields the following results:

$$b = 0.135,\ c = 0.0012,\ d = 0.005364,$$
$$v = 0.0001475,\ k = 3.950,\ x = 10 \text{ and } m = 0.8712.$$

These parameters were identified via a multidimensional grid search. Accordingly, we computed 500 simulation runs for each parameter setting. The length of each time series comprises $T = 12,800$ observations, reflecting a time span of 51 years with about 250 daily observations per year. The only exception is the calculation of the distortion, which is based on $T = 36,250$ observations, corresponding to a time span of 145 years. The lengths of the simulated data sets are thus comparable to the lengths of the data sets we have for the S&P500. As it turns out, the average moment matching score

[3] Our objective function is related to the joint moment coverage ratio (=JMCR) used in Franke and Westerhoff (2012). Their aim is to maximize the fraction of simulation runs for which model-generated moments jointly drop into the 95 percent confidence intervals of their empirical counterparts. Alternatively, one may use an objective function which minimizes the average of the (squared) deviations between the empirical moments and the model-generated moments, using an appropriate weighting scheme. For pioneering contributions in this direction see, for instance, Gilli and Winker (2003) and Franke (2009). Although the method of simulated moments is a powerful tool to estimate small-scale agent-based models, it requires a number of subjective choices with respect to specifying the objective function and selecting moments. We hope that our objective function stimulates more work in this important line of research.

for the above parameter setting reaches an astonishing value of $AMMS = 0.855$, i.e. the simulated model moments drop on average in 85.5 percent of the cases in the 95 percent confidence intervals of their empirical counterparts. Since any further change of an individual model parameter would result in an $AMMS$ loss, we can conclude that we have found at least a local $AMMS$ maximum.[4]

$AMMS$	0.855
D	0.842
V	0.906
$\alpha_{5.0}$	0.804
$ac\ r_1$	0.996
$ac\ r_2$	0.814
$ac\ r_3$	0.994
$ac\ \|r_3\|$	0.974
$ac\ \|r_6\|$	0.972
$ac\ \|r_{12}\|$	0.968
$ac\ \|r_{25}\|$	0.836
$ac\ \|r_{50}\|$	0.754
$ac\ \|r_{100}\|$	0.404

Table 2: Overview of the model's moment matching. The table shows the average moment matching score (= $AMMS$) and the matching of the 12 individual moments. Estimations are based on 500 simulation runs.

Before discussing how the model's parameters affect its performance, we briefly study how well our model matches the 12 individual moments. For instance, Table 2 reveals that the distortion, the volatility and the tail index fall in 84.2 percent, 90.6 percent and 80.4 percent of the cases in the 95 percent confidence intervals of their empirical counterparts. We may thus argue that our model is able to produce reasonable levels of distortion and volatility and fat-tailed return distributions. The moment matching of the autocorrelation coefficients of raw returns at lags 1, 2 and 3 scatters between 81.4 percent and 99.6 percent, suggesting that the model's price dynamics resembles a random walk. The individual average scores of the autocorrelation

[4]Since we use a numerical grid-search procedure, it remains unclear whether there are better local maxima or whether we have already arrived at the global maximum. Thus, our $AMMS$ of 85.5 percent should be regarded as a lower boundary for the performance of our model.

coefficients of absolute returns at lags 3, 6 and 12 are above 95 percent; the individual average scores at lags 25, 50 and 100 are distributed between 83.6 percent and 40.4 percent. Hence, the model's ability to generate volatility clustering is exceptionally good for lags 3, 6 and 12, yet appears to be somewhat limited for lags 25, 50 and 100.

However, the model's performance looks even better if we take into account the whole distributions of the 12 simulated moments. Table 3 therefore shows the median and the lower and upper boundaries of the 95 percent confidence intervals of the 12 simulated moments. Most importantly, we now see that in 97.5 percent of the simulation runs, the autocorrelation coefficient of absolute returns at lag 100 is larger than 0.03. Since the 95 percent significance band of raw and absolute returns' autocorrelation coefficients, assuming a white noise process, is about $\pm 2/\sqrt{12,800} \approx \pm 0.02$, we can conclude that almost all simulation runs display long-range volatility clustering effects. Table 3 also shows that the tail index is below 3.92 in 97.5 percent of the simulation runs. Since Lux and Ausloos (2002) argue that the tail index of major financial markets hovers between 3 and 4, the matching of the distribution of returns may also be regarded as satisfactory.

	D	V	$\alpha_{5.0}$	$ac\ r_1$	$ac\ r_2$	$ac\ r_3$
Median	0.304	0.720	3.450	0.010	0.000	0.000
Lower bound	0.228	0.650	3.130	-0.010	-0.030	-0.030
Upper bound	0.388	0.800	3.920	0.040	0.020	0.030

	$ac\ \lvert r_3\rvert$	$ac\ \lvert r_6\rvert$	$ac\ \lvert r_{12}\rvert$	$ac\ \lvert r_{25}\rvert$	$ac\ \lvert r_{50}\rvert$	$ac\ \lvert r_{100}\rvert$
Median	0.250	0.250	0.230	0.200	0.150	0.080
Lower bound	0.220	0.210	0.190	0.150	0.100	0.030
Upper bound	0.280	0.270	0.260	0.230	0.190	0.130

Table 3: The frequency distributions of the model's moments. The first line contains estimates of the median of the distortion D, the volatility V, the tail index $\alpha_{5.0}$, 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 $i \in \{3, 6, 12, 25, 30, 100\}$. The second and third lines show the lower and upper boundaries of the 95% conficence intervals of the 12 simulated moments. Estimations are based on 500 simulation runs.

To visualize the matching of the 12 individual moments, we plot the smoothed distributions of the simulated moments (black lines) and the smoothed distributions of the empirical moments (shaded in gray) in Figure 2. Accordingly, the matching of the volatility, the distortion, the autocorrelation coefficients of raw returns at lags 1 and 3, and the autocorrelation coefficients of absolute returns at lags 3, 6, 12, 25 and 50 immediately appears to be quite acceptable. As already mentioned, the autocorrelation coefficients of absolute returns at lag 100 are, on average, lower than their empirical counterparts but almost all of them are statistically significant. Moreover, almost all tail indices are below 4. The only moment we have not yet discussed is the autocorrelation coefficient of raw returns at lag 2. Note that the distribution of the empirical moment is centered around $ac\ r_2 = -0.033$ (see also Table 1) while the distribution of the simulated moment is centered around $ac\ r_2 = 0$ (see also Table 3). Since a stock market's return dynamics usually shows no signs of predictability, our results are in line with what one would like to see from a theoretical point of view.

Figure 3 suggests that our model parameters are well identified. For instance, the top left panel shows how the $AMMS$ depends on the average reaction parameter of the speculators' technical trading component. Unless stated otherwise, we use 500 simulation runs to compute the $AMMS$. Moreover, each parameter is increased in 10 discrete steps and for each parameter combination we use the same seeds of random variables. As can be seen, if we deviate from $b = 0.0135$, the average moment matching score decreases. The main reason for this is that changing parameter b affects the matching of the autocorrelation coefficients of raw returns. For instance, increasing parameter b from its current position adds predictability to the model's return dynamics, a feature which is absent in actual data. The top right panel shows a similar result for the average reaction parameter of the speculators' fundamental trading component. Note that parameter c mainly affects the model's ability to produce a realistic level of distortion. If parameter c increases, the distortion shrinks; if parameter c decreases, the distortion increases. For $c = 0.0012$, the model matches the distortion of the S&P500 best and thus maximizes the $AMMS$.

The model's performance depends even more strongly on parameters d and v, as indicated in the second line of Figure 3. Even small changes in these two parameters can decrease the $AMMS$ substantially. Note that parameter d directly influences the overall volatility of the market while parameter v is critical for the model's regime switching behavior. Parameters d and v must therefore stand in a certain relation to each other to obtain realistic dynamics. For instance, if one seeks to calibrate the model to a higher volatility level, say for a more volatile stock market, parameters d and v must be increased simultaneously (unfortunately, the optimal relation between

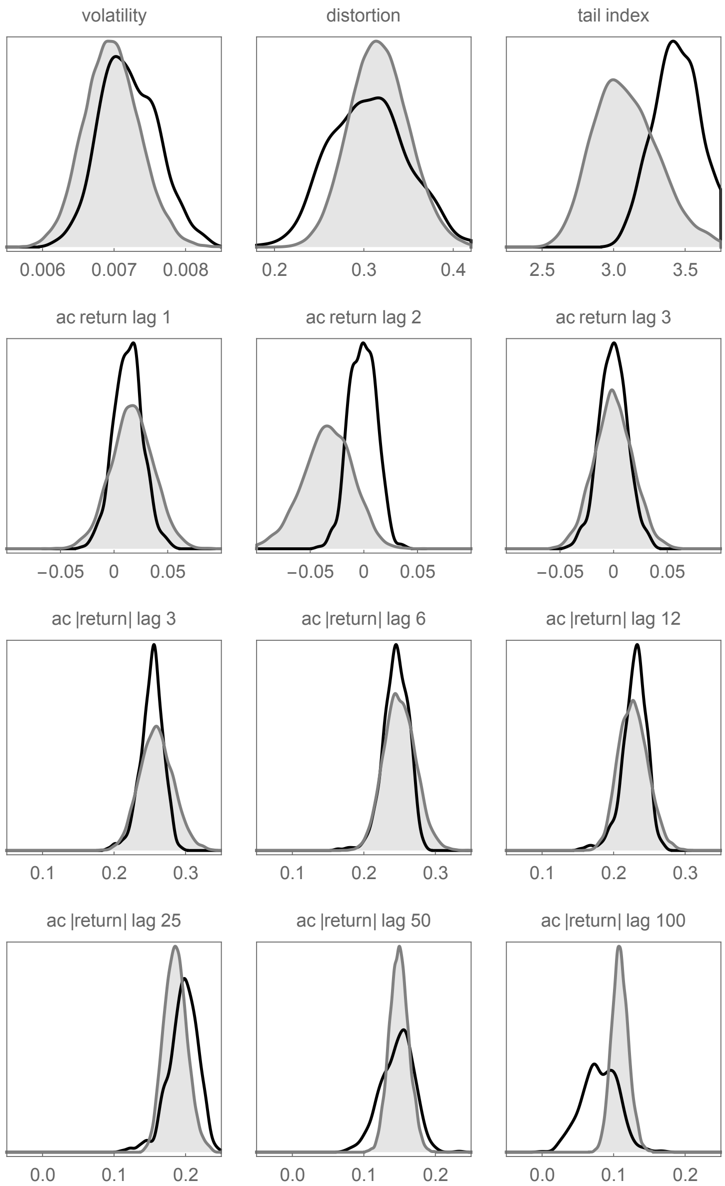

Figure 2: Distributions of simulated and empirical moments. The figure compares the smoothed distributions of the 12 simulated moments (black) with the bootstrapped distributions of their respective empirical counterparts (shaded in gray). Estimations of simulated moments are based on 500 simulation runs, while the bootstrapped distributions of empirical moments are obtained as described in Section 3.

d and v is not constant). Parameters k, x and m also influence the model's regime switching dynamics, and thus have an impact on a number of individual moments. Changing one of these parameters from its current position leads to a marked reduction in the $AMMS$. The bottom right panel of Figure 3 reveals that the $AMMS$

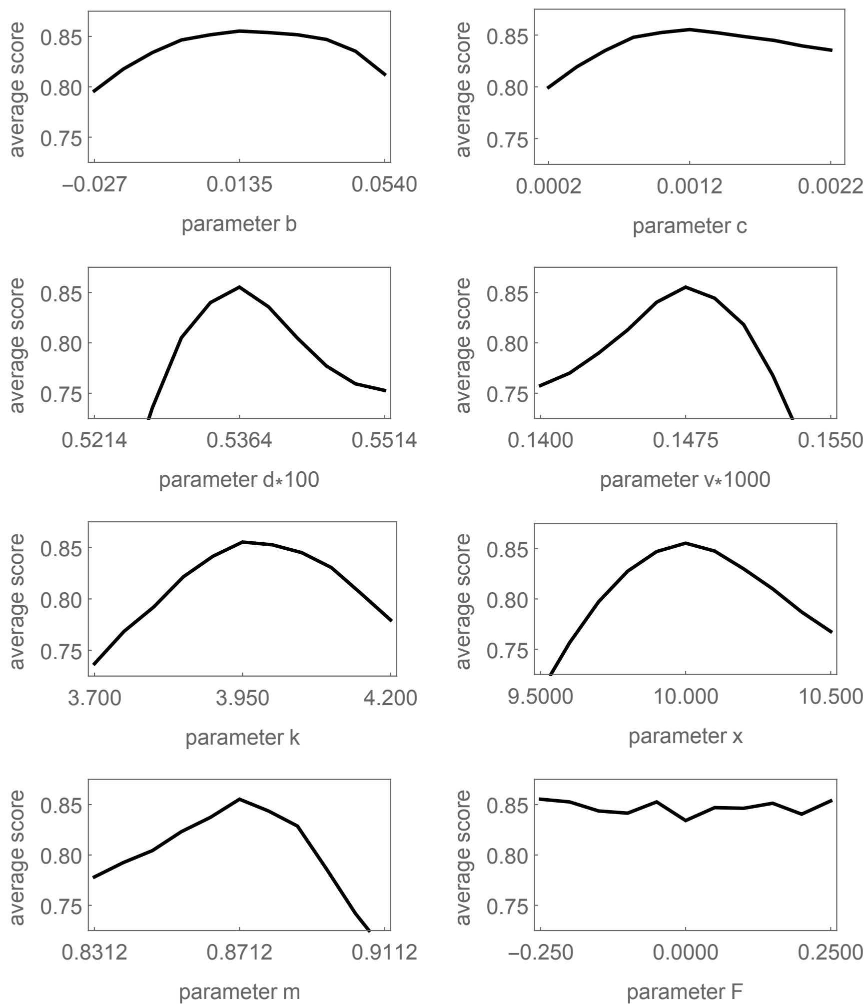

Figure 3: Identification of model parameters. The panels reveal how the $AMMS$ depends on the model's parameters. The $AMMS$ is computed on the basis of 500 siumulation runs. In the first seven panels, the same seeds of random variables are used while different seeds of random variables are used in the bottom right panel.

does not in fact depend on the level of the log fundamental value. However, in this panel we repeated the computation of the $AMMS$ for different values of parameter F with different seeds of random variables. Note that the $AMMS$ fluctuates in a narrow band around 85 percent. Compared to the other seven panels, we observe that single parameter changes always result in stronger changes in the $AMMS$ than the randomly inflicted changes in the $AMMS$ depicted in the bottom right panel. In this sense, the effects of the seven model parameters on the model's performance may be deemed to be significant.

4.2. The functioning of the model

To understand the functioning of our model, it is helpful to explore one particular simulation run in more detail. We therefore depict in Figure 4 a representative simulation run of our model with a sample length of $T = 12,800$ observations. The top panel shows the evolution of the log price in the time domain. As can be seen, there are boom and bust periods, i.e. the price fluctuates in an intricate manner around its fundamental value. This panel is comparable to the second panel of Figure 1 (except that we now look at a time span of 51 years instead of a time span of 145 years). However, the amplitudes of the price swings are on a similar level, and we know already from the statistical analysis provided in Section 4.1 that our model matches the average distortion of the S&P500 quite well. The explanation for the model's oscillatory price behavior is quite simple. While the technical and random demand components tend to drive the price away from its fundamental value, the fundamental demand component ensures that the price eventually reverts to its fundamental value. Recall that the fundamental demand component has a cubic nature, i.e. the mean reversion pressure increases with the distortion.[5]

The second panel of Figure 4 shows the model's return dynamics. Besides a high average volatility, we also notice a number of larger returns and several volatility outbursts. The third panel of Figure 4, depicting the development of X_t, explains these phenomena. Suppose that the volatility in the market is low so that speculators trade more or less independently. Technically, this means that X_t is rather low and that the random trading signals are hardly correlated. Large parts of the speculators' orders then cancel out, i.e. the market maker faces a relatively balanced excess demand. As a result, the market maker adjusts prices only weakly and volatility remains low. However, speculators may even receive in a low volatility regime a sequence of stronger trading signals. Their increased trading behavior then forces the market maker to adjust prices more strongly. As the market's volatility increases, speculators start to display a stronger herding behavior. Unsure about what is going on, they copy the behavior of others. Technically, X_t is now rather high, i.e. the speculators' random trading signals are correlated. Since a synchronized trading behavior leads to a less balanced excess demand, the market maker continues to adjust prices more strongly. Clearly, the high volatility regime becomes persistent. Even in a

[5]Further simulations reveal that a linear fundamental demand component is less able to match the S&P500's distortion.

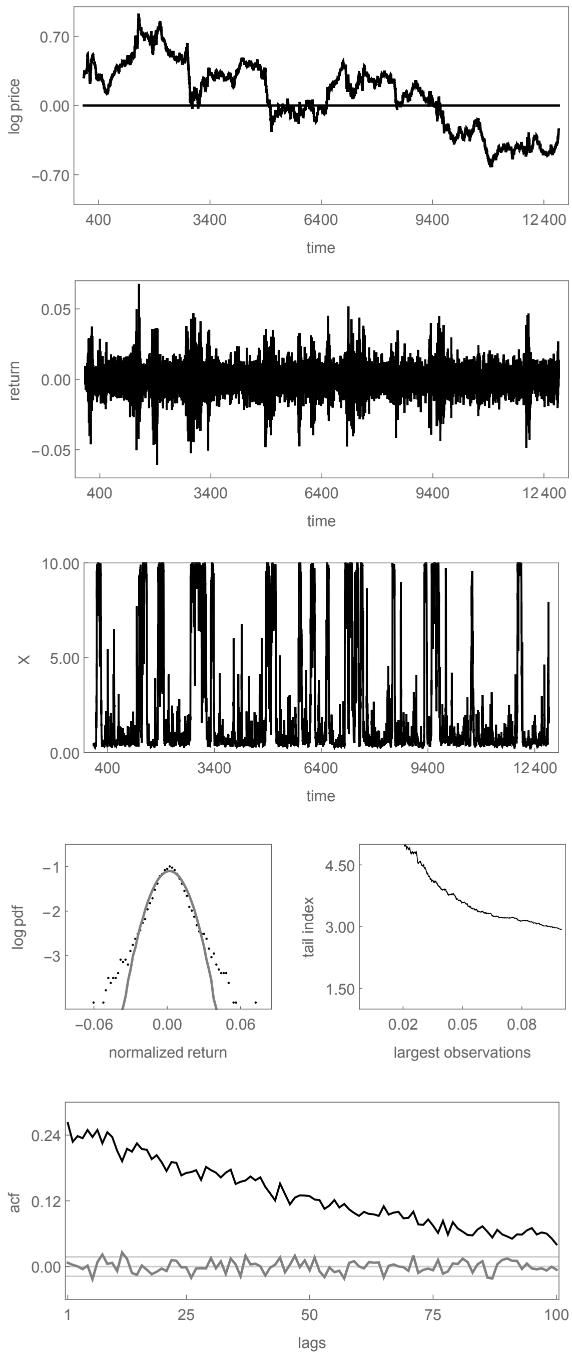

Figure 4: The dynamics of the model. The panels show, from top to bottom, the evolution of the log price, the returns, the strength of speculators' coordination behavior, the log distribution of normalized returns, the Hill tail index estimator as a function of the largest returns and the autocorrelation function of raw returns (gray line) together with the autocorrelation function of absolute returns (black line), respectively. The simulation run is based on 12,800 observations.

high volatility regime, a sequence of trading days when speculators receive only weak trading signals may eventually occur. Speculators' excess demand then decreases, as does the market maker's price adjustment. Since volatility ebbs away, speculators start to relax. Behaving more independently further weakens speculators' excess demand, and the market maker continues to adjust prices only weakly. Volatility then remains persistently low - until speculators receive again a sequence of stronger trading signals.

Since the volatility outburst may result in larger price changes, the model also gives rise to fat-tailed return distributions. This can be detected from the left panel of the fourth line of Figure 4. As in the case of the S&P500 (see left panel of the fourth line of Figure 1), extreme returns occur more frequently than warranted by the normal distribution. The right panel of the fourth line shows the tail index as a function of the tail fraction. Taking into account the largest 5 percent of the observations, we observe a tail index of about 3.59.[6] The final panel of Figure 4 shows the autocorrelation functions of absolute returns and of raw returns. Our observations are quite comparable to what we observe for the S&P500. Raw returns are basically serially uncorrelated while the autocorrelation coefficients of absolute returns are clearly significant, even for lags up to 100 periods. All in all, we find the simulated dynamics to be strikingly similar to the actual behavior of financial markets.

5. Conclusions

We propose a novel agent-based financial market model to explain the dynamics of financial markets. To be precise, we consider a stock market which is populated by a market maker and a fixed number of heterogeneous speculators. The market maker adjusts the stock's price with respect to excess demand while speculators rely on a mix of technical and fundamental trading rules to determine their orders. We model the heterogeneity of the trading rules applied by adding a multivariate normal distributed random variable to speculators' trading rules. Guided by empirical and experimental work, we assume that speculators observe other speculators' actions in

[6]While our estimated model systematically produces tail indices below 4 for a tail fraction of 5 percent, it does not produce tail indices of comparable size for smaller tail fractions. However, it seems to us that virtually no other agent-based models of a comparable size performs significantly better than our model.

periods of heightened uncertainty more strongly. Note that such herding behavior implies a decrease in the heterogeneity of the trading rules applied. To take this into account, we assume that the correlation between speculators' random trading signals increases with the market's past volatility.

Fortunately, our approach allows a convenient aggregation of speculators' trading behavior. Since the dynamics of our model depends on three equations only, we can use the method of simulated moments to estimate its parameters. For this purpose, we define 12 summary statistics (moments) to quantify five important stylized facts of financial markets. In particular, we rely on a distortion measure to capture the stock market's boom-bust dynamics, a volatility measure to capture the stock market's average variability, a tail index to capture the fat-tailedness of the stock market's return distribution, three autocorrelation coefficients of raw returns to capture the random walk property of the stock market and six autocorrelation coefficients of absolute returns to capture the stock market's volatility clustering behavior. Our empirical analysis focuses on the S&P500. Here we are fortunate to have access to 145 years of monthly data to identify the stock market's distortion and 51 years of daily data to characterize the other phenomena. Based on our 12 summary statistics, we define a goodness-of-fit criterion which indicates the effectiveness of the model's average moment matching. As it turns out, our estimated model achieves an astonishing AMMS of around 85 percent, i.e. on average, about 85 percent of the model-implied moments drop into the 95 percent confidence intervals of their empirical counterparts.

Speculators' herding behavior is crucial for the model's ability to produce realistic dynamics. The key message delivered by our model may be summarized as follows. Consider a situation in which the stock market's volatility is low. In such a situation, speculators trade more or less independently from each other, i.e. speculators' trading behavior is relatively heterogeneous. As a result, many orders placed by speculators offset each other and excess demand is rather balanced. Consequently, the market maker's price adjustment is modest and volatility remains low. Eventually, however, there appears a sequence of trading days when speculators happen to receive stronger trading signals. Their increased trading intensity amplifies excess demand so that the market maker adjusts prices more strongly. At this point, the low volatility regime turns into a high volatility regime. Speculators become nervous and start to observe other speculators' actions more closely. The synchronization of speculators' trading behavior leads to a persistently high excess demand and a sustained period of significant price changes. Eventually, however, there appears a sequence of trading days when speculators receive weak trading signals. Although their trading behavior remains coordinated, excess demand decreases and the market maker adjusts prices less forcefully. As volatility decreases, speculators start to relax and behave more independently. Now the market enters a period of low volatility until speculators once again receive a sequence of stronger trading signals.

Our approach may be extended in various ways, and we conclude our paper by pointing out four avenues for future research. First, one may assume that speculators' herding behavior depends not only on the stock market's volatility but also on its distortion. The more the stock price deviates from its fundamental value, the more risky the stock market may appear to speculators. Second, while our estimated model is able to generate fat-tailed return distributions, it does not produce extreme market changes. In Schmitt and Westerhoff (2015), we assume that exogenously occurring sunspots, such as investment advice by financial gurus, may coordinate the trading behavior of speculators. If sufficiently many speculators trade in the same direction, extreme market changes may occur. Put differently, one may easily condition the correlation between speculators' random trading signals on additional influence factors. Third, our model may be used to explore which types of policy tools may be used to stabilize financial markets. For instance, our model suggests that a policy which manages to reduce the stock market's volatility automatically relaxes speculators' herding behavior and should thereby enhance market stability. Fourth, we determined the parameters of our model by maximizing the model's average moment matching score. Of course, different objective functions may be used to estimate our model. In this paper, we opt for an egalitarian treatment of the moments. Alternatively, one could search for a parameter setting which maximizes the worst performing summary statistic. Similarly, one may reconsider the choice of summary statistics. We would like to remark at this point that we know of no other study which also uses Shiller's (2015) data to quantify stock market mispricing. We are under the impression that, in order to make the most out of the method of simulated moments, it would be useful to experiment further with the objective function and the underlying summary statistics. To sum up, our simple agent-based model reveals that herding behavior can reduce the heterogeneity of the trading rules applied and thereby amplify stock price changes. To make the functioning of our model as clear as possible, we ensure maximum simplicity. However, we hope that our paper will stimulate more work in this exciting research direction.

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