This research was carried out in the Bamberg Doctoral Research Group on Behavioral Macroeconomics (BaGBeM) supported by the Hans-Böckler Foundation (PK 045)

PK 045 PROMOTIONSKOLLEG

Gefördert durch die Hans Böckler Stiftung

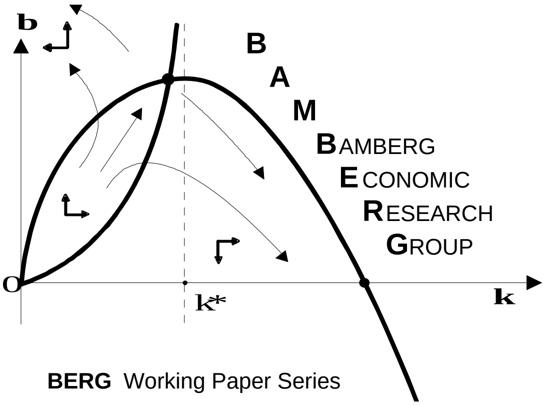
Mitbestimmung · Forschung · Stipendien

Heterogeneous speculators and stock market dynamics: a simple agent-based computational model

Noemi Schmitt, Ivonne Schwartz and Frank Westerhoff

Working Paper No. 160

July 2020



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 978-3-943153-81-1

Redaktion:
Dr. Felix Stübben*

* felix.stuebben@uni-bamberg.de

Heterogeneous speculators and stock market dynamics: a simple agent-based computational model

Noemi Schmitt, Ivonne Schwartz and Frank Westerhoff*

Department of Economics, University of Bamberg, Germany

Abstract

We propose a simple agent-based computational model in which speculators' trading behavior may cause bubbles and crashes, excess volatility, serially uncorrelated returns, fat-tailed return distributions and volatility clustering, thereby replicating five important stylized facts of stock markets. Since each speculator bets on his own (technical and fundamental) trading signals, stock prices are excessively volatile and oscillate erratically around their fundamental value. However, speculators' heterogeneity occasionally vanishes, e.g. due to panic-induced herding behavior, yielding extreme returns. Lasting regimes with high volatility originate from the fact that speculators extract stronger trading signals out of past stock price movements when stock prices fluctuate strongly. Simulations furthermore suggest that circuit breakers may be an effective tool to combat financial market turbulences.

Keywords

Stock markets; stylized facts; agent-based computational models; technical and fundamental analysis; circuit breakers; econophysics.

JEL classification

C63; D84; G15.

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

1 Introduction

We propose a simple agent-based computational model to explain a number of important stylized facts of stock markets. In a nutshell, our model and our main results may be summarized as follows. We consider a stock market that is populated by a market maker and a given number of heterogeneous interacting speculators. The market maker adjusts stock prices with respect to the excess demand of speculators who, in turn, determine their orders by following their own individual trading signals, derived either from private market research or from applying complex (algorithmic) trading systems. Simulations reveal that speculators' trading behavior may generate bubbles and crashes, excess volatility, serially uncorrelated (log) stock price changes, fat-tailed return distributions and lasting volatility outbursts. Since speculators bet on technical and fundamental trading signals, stock prices are excessively volatile and circle in an apparently random fashion around their fundamental value. Extreme returns occur in our model due to a sporadic loss of heterogeneity. To be precise, there are short-lived periods in which speculators' behavior becomes coordinated, e.g. because they react to the same trading signals, hard-wired into their trading systems, or because they display panic-induced herding behavior, e.g. caused by sharp stock price changes. Lasting periods of high volatility occur when speculators persistently receive strong trading signals. Since many speculators infer their trading signals out of past stock price movements, the latter occurs in periods characterized by significant stock price changes. In such periods, speculators also tend to overreact to their own individual trading signals, which keeps volatility high. Our model also indicates that circuit breakers may be an effective tool to stabilize the dynamics of stock markets.

Our paper belongs to a well-developed field of literature that seeks to explain the dynamics of stock markets by taking an explicit agent-based perspective. Analytically tractable small-scale agent-based models, focusing on a few representative speculator types, have been proposed, for instance, by Zeeman (1974), Beja and Goldman (1980), Day and Huang (1990), Chiarella (1992), de Grauwe et al. (1993), Lux (1995), Farmer and Joshi (2002) and Chiarella and Iori (2002). More elaborated and simulation-oriented, large-scale agent-based models, studying the interplay between many different and evolving speculator types, have been advanced, for instance, by Palmer et al. (1994), Arthur et al.

(1997), LeBaron et al. (1999), Chen and Yeh (2001) and Raberto et al. (2001). While it is still important to better understand the forces that may create financial market havoc, current research increasingly addresses questions that revolve around input validation (Anufriev et al. 2016, Fagiolo et al. 2017, Guerini and Moneta 2017), model estimation (Lamperti et al. 2018, Platt 2020, Kukacka and Kristoufek 2020), policy applications (Stanek and Kukacka 2018, Diem et al. 2020, Schmitt et al. 2020) and prediction (Demirer et al. 2019, Zhang et al. 2019, Westphal and Sornette 2020). See Delli Gatti et al. (2018), Dieci and He (2018), Iori and Porter (2018) and Lux and Zwinkels (2018) for up-to-date surveys.

Recently, Schmitt and Westerhoff (2017a,b) and Schmitt (2020) started to develop rather simple agent-based computational stock market models by assuming that speculators' trading behavior can be represented at least partially by correlated random variables. For instance, Schmitt (2020) proposes an agent-based version of the asset-pricing model by Brock and Hommes (1998), keeping the correlation between speculators' random demand components constant. Nevertheless, her model produces lasting volatility outbursts when the mass of speculators switches towards destabilizing technical trading rules. Schmitt and Westerhoff (2017a) put forward an agent-based version of the asset-pricing model by Franke and Westerhoff (2012). Extreme price changes emerge within their model when the arrival of exogenous sunspots initiates a spontaneous coordination of speculators' trading behavior. Relatedly, Schmitt and Westerhoff (2017b) assume in their asset-pricing model that the correlation between speculators' trading behavior changes slowly with respect to the market's volatility. If volatility increases, speculators become afraid and follow the trading behavior of other speculators more closely. As a result, speculators' excess demand escalates, keeping volatility high. In our paper, we assume that endogenous market events may lead to a spontaneous coordination of speculators' trading behavior, and thus to extreme returns, while speculators' trading intensity depends positively on the market's volatility, an aspect that may produce lasting volatility outbursts.

Within our model, speculators' trading behavior contains a strong random component. In fact, we capture their trading behavior by a vector of multivariate normally distributed random variables to which we impose a certain minimalistic structure. Note that such a modeling strategy is quite common in certain areas of research, e.g. in econophysics. For instance, Cont and Bouchaud (2000) assume in their stock market model that the decisions of clusters of active speculators whether to buy or sell stocks are random variables with equal probabilities. See Stauffer and Penna (1998), Chang and Stauffer (1999), Stauffer and Sornette (1999), Stauffer and Jan (2000) and Iori (2002) for extensions and generalizations of this framework. Similarly, Gode and Sunder (1993, 1997), Daniels et al. (2003), Farmer et al. (2005a, b) and Ladley (2012) study stock market models that are driven by zero-intelligence agents who trade randomly, subject only to their budget constraints, demonstrating that important properties of stock markets depend less on agents' strategic (rational) behavior, and more on their institutional arrangements. More recent contributions in which speculators' behavior also contains a larger random component include, for instance, Ladley et al. (2015), Xing and Ladley (2019) and Ladley (2020).

The remainder of our paper is organized as follows. In Section 2, we present a simple agent-based computational model of the stock market. In Section 3, we compare the dynamics of our approach with the behavior of actual stock markets. In Section 4, we explain the model's functioning. In Section 5, we discuss possible effects of circuit breakers. In Section 6, we conclude our paper. A number of robustness checks are presented in Appendix A.

2 A simple agent-based computational stock market model

In this section, we develop a simple agent-based computational model that aims at explaining a number of important stylized facts of stock markets. Let us start with previewing the basic setup of our approach. We consider a single stock market that is populated by a market maker and a given number of heterogeneous interacting speculators. The market maker adjusts the price of the stock with respect to speculators' order flow. Each speculator bases her orders on her own individual trading signals, derived either from private market research or from applying complex (algorithmic) trading systems. For simplicity, we model speculators' trading signals as multivariate normally distributed random variables, imposing the following minimalistic structure. First, the means of the random variables reflect speculators' tendency to extrapolate past stock price changes and to bet on mean reversion. Second, the variances of the random variables represent speculators' trading intensities and increase in line with the stock market's volatility. Clearly, speculators infer stronger trading signals – or react more strongly to given trading signals – if the volatility of the stock market is high. The former argument is consistent with the observation that speculators derive trading signals out of past stock price movements and that the strength of these trading signals naturally grows with the stock market's volatility. The latter argument is in line with the observation that speculators tend to overreact to their trading signals in volatile periods, simply because they are agitated and thus regard their trading signals as more relevant in such times. Third, the correlation between speculators' trading signals increases if the stock market displays significant stock price patterns. This may be because speculators observe the behavior of others more strongly during periods of heightened uncertainty or because certain price patterns, such as significant reversals of stock price changes, are hard-wired into a sufficient number of speculators' complex (algorithmic) trading systems.

Let us now turn to the details of our model. We assume that a market maker adjusts the price of the stock with respect to the excess demand originating from the orders of N heterogeneous interacting speculators. As in Beja and Goldman (1980), Day and Huang (1990) and Farmer and Joshi (2002), the market maker's behavior is formalized as

$$P_{t+1} = P_t + a \sum_{i=1}^{N} D_{t,i}, \quad (1)$$

where P_t is the log price of the stock at time t, a is a positive price adjustment parameter, reflecting the stock market's liquidity, and $\sum_{i=1}^{N} D_{t,i}$ is the aggregate excess demand resulting from the individual orders $D_{t,i}$ of speculators $i = 1,2, \dots N$. Hence, if the sum of speculators' orders is positive (negative), the market maker increases (decreases) the log stock price.

The orders placed by speculator i depend on her own individual trading signals, derived either from private market research or by applying complex (algorithmic) trading systems. Inspired by the aforementioned line of research initiated by Gode and Sunder (1993) and Cont and Bouchaud (2000), we do not aim at formalizing speculators' trading behavior in detail. Instead, we simply represent speculator i's order in period t by

$$D_{t,i} = \delta_{t,i}, \quad (2)$$

where $\delta_t = \{\delta_{t,1}, \delta_{t,2}, \dots, \delta_{t,N}\}'$ is a vector of multivariate normally distributed random variables, i.e. $\delta_t \sim N(\mathrm{M}_t, \Sigma_t)$. We assume for the mean vector

$$\mathrm{M}_t = \{\mu_{t,1}, \mu_{t,2}, \dots, \mu_{t,N}\}' \tag{3}$$

and the variance-covariance matrix

$$\Sigma_t = \begin{bmatrix} \sigma_{t,1}^2 & \sigma_{t,1}\sigma_{t,2}\rho_{t,1,2} & & \cdots & \sigma_{t,1}\sigma_{t,N}\rho_{t,1,N} \\ \sigma_{t,2}\sigma_{t,1}\rho_{t,2,1} & \sigma_{t,2}^2 & & & \vdots \\ \vdots & & & \ddots & \sigma_{t,N-1}\sigma_{t,N}\rho_{t,N-1,N} \\ \sigma_{t,N}\sigma_{t,1}\rho_{t,N,1} & \cdots & \sigma_{t,N}\sigma_{t,N-1}\rho_{t,N,N-1} & & \sigma_{t,N}^2 \end{bmatrix} \tag{4}$$

that $\mu_t = \mu_{t,i}$, $\sigma_t^2 = \sigma_{t,i}^2$ and $\rho_t = \rho_{t,i,j}$ for $i, j = 1,2, \dots, N$ and $i \neq j$. Despite these restrictions, each speculator submits a different order to the market maker, unless, of course, $\rho_t = 1$. In that case, all speculators submit an identical order to the market maker.

The empirical and laboratory evidence reviewed by Menkhoff and Taylor (2007) and Hommes (2011) highlights the fact that speculators rely on technical and fundamental analysis to determine their orders. The key idea behind technical analysis (Lo et al. 2000) is that stock prices move in trends. Fundamental analysis (Graham and Dodd 1951), in contrast, postulates that stock prices display a tendency to return to their fundamental values. Let F denote the constant log fundamental value of the stock market. We thus assume that

$$\mu_t = b(P_t - P_{t-1}) + c(F - P_t). \tag{5}$$

Note that μ_t captures the core principles of technical and fundamental analysis. The first component of (5) suggests that speculators should place a buy (sell) order if the stock market goes up (down), while the second component of (4) recommends that they sell (buy) overvalued (undervalued) stocks. The reaction parameters $b, c > 0$ determine the strength of these trading signals.

Moreover, we assume that speculators' trading intensity increases with the stock market's volatility. This assumption is supported by two arguments. First, speculators make their beliefs about future stock prices (and hence their demand) dependent on past stock price movements. If there is considerable stock price variability, then their trading signals will grow correspondingly (Murphy 1999). Second, speculators overreact to their trading signals in periods of high volatility (Manzan and Westerhoff 2005). Let us capture the stock market's volatility by

$$V_t = dV_{t-1} + (1-d)(P_t - P_{t-1})^2, \tag{6}$$

where $0 < d < 1$ is a memory parameter. Moreover, let $\bar{V} > 0$ be a reference value for the stock market's volatility. We model the intensity of speculators' trading behavior by specifying σ_t^2 as

$$\sigma_t^2 = e^l + \frac{e^h - e^l}{1 + \exp[e^s(V_t - \bar{V})]}. \tag{7}$$

Note that (7) represents a logistic function that is bounded between $0 < e^l < e^h$. For $V_t = \bar{V}$, speculators' trading intensity is equal to the midpoint of (7), i.e. $\sigma_t^2 = (e^l + e^h)/2$. The slope parameter $e^s > 0$ of (7) determines how sensitively σ_t^2 reacts to a change in V_t. Economically, the S-shaped function (7) implies that speculators' trading intensity increases in line with the stock market's volatility.[1]

However, speculators are not isolated in their decision-making. As already observed by Keynes (1936), speculators tend to herd together in periods of heightened uncertainty. Moreover, it seems that certain price patterns are hard-wired into speculators' complex (algorithmic) trading systems. If such a price pattern emerges, speculators' trading systems generate correlated trading signals.[2] In reality, there may be many price/return patterns that initiate correlated actions among market participants. To keep things as simple as possible, however, we assume that the correlation of speculators' trading behavior depends on the strength of a single condition, given by

$$C_t = ((P_t - P_{t-1}) - (P_{t-1} - P_{t-2}))^2. \tag{8}$$

According to (8), C_t may take a particularly large value when a significant reversal of stock price changes occurs; say when a four percent price drop is followed by a three percent price increase. Clearly, a more developed version of our model may incorporate more

---

[1] According to Murphy (1999), the reliability of technical trading signals increases with the trading volume of a stock market, i.e. a high trading volume indicates that the current trading signal is strong whereas a low trading volume indicates that the current trading signal is weak. Since simulations reveal that our model produces a high contemporaneous correlation between trading volume and volatility, an interesting model extension could be to condition speculators' trading intensity on the trading volume of the stock market. See Westerhoff (2006) for an example in that direction.

[2] A well-known example in this respect concerns the stock market crash of October 1987, which, according to Greenwald and Stein (1991), Harris (1998) and Shiller (2015), was at least partially triggered by computer (program) trading, and could have been stopped by circuit breakers. More recent examples include the occurrence of so-called flash crashes, amplified by high-frequency traders who follow computerized trading systems. See Jacob Leal et al. (2016) and Jacob Leal and Napoletano (2019) for empirical evidence and interesting modeling approaches. Gomber and Zimmermann (2018) and Vassiloadis and Dounias (2018) provide insightful overviews of complex (algorithmic) trading systems.

than one condition. Moreover, these conditions may then evolve over time and/or contain probabilistic components.[3] The correlation between speculators' trading behavior is formalized as

$$\rho_t = f^l + \frac{f^h - f^l}{1 + \exp[f^s(C_t - \bar{C})]}, \tag{9}$$

where f^l and f^h determine the lower and upper boundary of ρ_t, with $0 \leq f^l < f^h \leq 1$, $f^s > 0$ describes the slope of (9), and $\bar{C} > 0$ marks the position of its midpoint. The greater the value of condition (8), the stronger the correlation of speculators' trading behavior. If ρ_t approaches 1, speculators' trading signals become fully correlated and, consequently, they submit identical orders. If ρ_t approaches 0, speculators' trading behavior becomes uncorrelated, implying that a substantial part of their orders cancel each other out.

In principle, we can simulate the dynamics of our simple agent-based computational stock market model by using (1) to (9). For a larger number of speculators, however, simulations soon become rather time-consuming. Fortunately, our assumptions about speculators' trading behavior conveniently enable us to summarize their excess demand by

$$\sum_{i=1}^{N} D_{t,i} = N\big(b(P_t - P_{t-1}) + c(F - P_t)\big) + \sigma_t \sqrt{N + N(N-1)\rho_t}\, \varepsilon_t, \tag{10}$$

where $\varepsilon_t \sim N(0,1)$. As a result, we can therefore also simulate the model's dynamics by iterating the following stochastic nonlinear dynamical system:

$$\begin{cases} P_{t+1} = P_t + a\Big\{N\big(b(P_t - P_{t-1}) + c(F - P_t)\big) + \sigma_t \sqrt{N + N(N-1)\rho_t}\, \varepsilon_t\Big\} \\ \sigma_t^2 = e^l + \frac{e^h - e^l}{1 + \exp[e^s(V_t - \bar{V})]} \\ V_t = dV_{t-1} + (1-d)(P_t - P_{t-1})^2 \\ \rho_t = f^l + \frac{f^h - f^l}{1 + \exp[f^s(C_t - \bar{C})]} \\ C_t = ((P_t - P_{t-1}) - (P_{t-1} - P_{t-2}))^2 \end{cases} . \tag{11}$$

Note that speculators' excess demand, and, therefore, the market maker's price

---

[3] As we will see in the next section, however, one condition may already be sufficient for our model to produce extreme price changes and, consequently, fat-tailed return distributions. We remark that we also experimented with other conditions. For instance, similar dynamics to those discussed in the next section may be observed if (8) is replaced by $C_t = gC_{t-1} + (1-g)(P_t - P_{t-1})^2$, where $0 < g < 1$ is a memory parameter. In relation to (6), however, our simulations suggest that the memory parameter has to be set to a rather low value, say $g = 0.05$, implying that coordination among market participants critically hinges on the stock market's short-run behavior. To save one parameter, we opted for specification (8). Of course, this aspect deserves more attention in future work, in particular along the lines indicated above.

adjustment, increases with σ_t^2 and ρ_t, which, in turn, depend on V_t and on C_t, respectively.[4] It might be helpful to realize that V_t changes only slowly over time, provided that the memory parameter d is not too small. As a result, speculators' trading intensity remains high during turbulent market periods, keeping volatility high. In contrast, C_t may change quickly and take larger values only for brief moments of time. In such an event, speculators' trading behavior becomes correlated and a larger price change may occur. This is exactly what we will see when we simulate our model in the next section.

3 Time series properties of actual and simulated stock markets

Before we turn to the dynamics of our model, let us briefly recap the behavior of actual stock markets. As is well known, actual stock markets are characterized by a number of prominent stylized facts, including (i) bubbles and crashes, (ii) excess volatility, (iii) fat-tailed return distributions, (iv) serially uncorrelated returns and (v) volatility clustering. See Mantegna and Stanley (2000), Cont (2001) and Lux and Ausloos (2002) for detailed reviews. In the following, we briefly visualize the dynamics of three major stock markets. The left panels of Figure 1 depict the evolution of the DAX, the NIKKEI and the DJI from 1980 to 2019. Each time series, downloaded from Refinitiv Datastream, comprises about 10,000 daily observations. Despite the long-run upward trends of the DAX and the DJI, the boom-bust nature of all three stock markets is clearly striking.[5] The right panels of Figure 1 present the corresponding return dynamics, defined as log price changes. Obviously, actual stock markets are quite volatile. For instance, the standard deviations of the return time series of the DAX, the NIKKEI and the DJI are given by 0.013, 0.017 and 0.011, respectively. Moreover, there are a number of larger price changes. In

[4] The excess demand also increases with the number of speculators. For $a = \alpha/N$ and $N \rightarrow \infty$, however, the price adjustment equation reads $P_{t+1} = P_t + \alpha\{\left(b(P_t - P_{t-1}) + c(F - P_t)\right) + \sigma_t\sqrt{\rho_t}\,\varepsilon_t\}$. Hence, it is possible to rescale our model such that its dynamics does not depend on the number of speculators. While we prefer to keep N as a model parameter, it might be worthwhile to try to endogenize the number of (active) speculators in future work. See Iori (2002), Alfi et al. (2009), Blaurock et al. (2018) and Dieci et al. (2018) for examples in this direction.

[5] Bubbles and crashes are difficult to identify in real stock markets. However, Galbraiht (1994), Kindleberger and Aliber (2011) and Shiller (2015) stress that bubbles and crashes do exist in these markets. See Schmitt and Westerhoff (2017c) and Majewski et al. (2020) for attempts on how to capture the mispricing of actual stock markets.

particular, the DJI produced the largest daily loss (25.6 percent), while the NIKKEI produced the largest daily gain (13.2 percent). It is also apparent that periods of low volatility alternate with periods of high volatility.

******* Figure 1 about here *******

Figure 2 documents a number of distributional and correlation properties of the DAX, the NIKKEI and the DJI, using the same color coding as in Figure 1. The top left panel of Figure 2 compares the distributions of normalized stock market returns with the distribution of standard normally distributed returns (black line). The top right panel of Figure 2 shows the same, except that we present the evidence on a log-linear scale. As can be seen, the distributions of actual stock market returns are unimodal, almost symmetric and bell-shaped. Relative to the standard normal distribution, however, the distributions of actual stock market returns possess more probability mass in the center and in the tails. This is also evident from the center left panel of Figure 2, which illustrates the cumulative distributions of normalized actual stock market returns together with the cumulative distribution of standard normally distributed returns (black line) on a log-log scale. The outer parts of the distribution of actual stock market returns can be surprisingly well fitted by a power law in the form $prob(|return| > x) \approx cx^{-\alpha}$, where α is the so-called tail index. Note that a smaller tail index indicates fatter tails. In the center right panel of Figure 2, we plot the Hill tail index estimator (Hill 1975) as a function of the largest returns in percent. Using the largest 5 percent of the observations, for instance, the tail index for the DAX, the NIKKEI and the DJI is given by 3.07, 3.09 and 3.20, respectively.[6] The bottom left panel of Figure 2 shows the autocorrelation functions of raw returns (the gray lines represent the 95 percent confidence band). As can be seen, the autocorrelation coefficients of raw returns are not significant for almost all lags, indicating that the paths of the DAX, the NIKKEI and the DJI are close to a random walk. The bottom right panel of Figure 2 reports the autocorrelation coefficients of absolute returns. Since the autocorrelation coefficients of absolute returns are significant for more than 100 lags, we can conclude that volatility outbursts are quite persistent.

******* Figure 2 about here *******

[6] Such estimates are representative for many different financial markets, see, e.g. Gopikrishnan et al. (1999) and Plearou et al. (1999).

Let us now illustrate the extent to which our simple agent-based computational model can replicate the dynamics of actual stock markets (a more detailed robustness analysis is presented in Appendix A). For this purpose, we have to determine the model's 14 parameters. In the first step, we decided to set $N = 100$, $F = 0$ and $a = 1$. Roughly speaking, parameters N and a are scaling parameters, while parameter F merely determines the level around which stock price fluctuations take place. Assuming furthermore that $e^s = f^s = \infty$ implies that the intensity of and the correlation between speculators' trading signals jumps between their lower and upper boundaries. To fix the remaining nine model parameters, we conducted a tedious trial-and-error calibration exercise. In the end, we arrived at the following parameter values: $b = 0.00005$, $c = 0.00001$, $d = 0.87$, $e^l = 0.00000055$, $e^h = 0.00000245$, $\bar{V} = 0.000125$, $f^l = 0.0006$, $f^h = 0.055$ and $\bar{C} = 0.00257$. Future work may try to estimate our model, e.g. via the method of simulated moments, as discussed by Franke and Westerhoff (2012, 2016) and Schmitt and Westerhoff (2017a, b).[7]

Figures 3 and 4 portray the dynamics of three representative simulation runs. Each simulation run comprises 10,000 observations, corresponding to a time span of 40 years with 250 trading days per year. The first, second and third simulation runs differ only with respect to their random seeds. For comparability reasons, we selected the same layout for Figures 3 and 4 as we did for Figures 1 and 2. The left panels of Figure 3 show the evolution of three simulated stock markets in the time domain. As can be seen, simulated stock prices oscillate around their constant fundamental value, given by $\exp[F] = 1$. The amplitude of the boom-bust dynamics suggests that simulated stock prices tend to be "a factor 2" away from the fundamental value, a relation that is reported by Black (1986), Bouchaud et al. (2017) and Majewski et al. (2020) for actual stock markets, along with evidence that a self-correction of mispricing in stock markets can take several years.[8] Note that mispricing in the simulated stock market is also quite persistent. The right panels depict the corresponding return dynamics. On average, volatility is quite high in the

[7] Of course, other estimation methods may also be useful, see, e.g., the work by Lamperti et al. (2018), Platt (2020), Kukacka and Kristoufek (2020) and Bertschinger and Mozzhorin (2020).

[8] The famous "factor 2" rule by Black (1986, p. 533) implies that the stock "price is more than half of value and less than twice value". For our case, simulated stock prices should thus fluctuate in the interval $0.5 < F = 1 < 2$.

simulated stock markets. Although the fundamental value is constant, the standard deviations of the three return time series are given by 0.0124 (top), 0.0118 (center) and 0.0117 (bottom), comparable to those reported for the DAX, the NIKKEI and the DJI. The same is true for extreme price changes, given, for instance, by 15.3 percent and -13 percent for the first simulation run.

******* Figure 3 about here *******

The first three panels of Figure 4 show that the distributions of simulated stock market returns are bell-shaped, yet possess more probability mass in their tails than warranted by a normal distribution. From the center right panel of Figure 4, we can conclude that the tail indices for the three simulated time series, taking again the largest 5 percent of the returns into account, range between 3.28 and 3.53, only somewhat higher than their empirical counterparts. As revealed by the bottom right panels of Figure 4, returns hardly display any kind of serial correlation, i.e. the evolution of simulated stock markets is close to a random walk. Accordingly, it is difficult to “beat the market”, an important (economic) property that holds for actual and simulated stock markets. The bottom right panel reveals that the autocorrelation coefficients of absolute returns are highly significant, up to 100 lags. Of course, the ability of our simple agent-based computational stock market model to produce volatility clustering is already apparent from its return dynamics, depicted in Figure 3.

******* Figure 4 about here *******

The Monte-Carlo study presented in Appendix A.1 suggests that we may indeed regard the simulation runs discussed above as representative simulation runs. Overall, we can thus conclude that our simple agent-based computational stock market model is able to match the stylized facts of stock markets in a systematic and robust manner.

4 Functioning of the model

Let us now explain the functioning of our model. Figure 5 depicts a snapshot of the dynamics of the first simulation run (750 observations, ranging from period 4351 to 5100). The left panels show the evolution of simulated stock prices and returns while the right panels show speculators’ trading intensity (variance) and their coordination (correlation).

Based on these panels, our model's ability to match the stylized facts of stock markets may be understood as follows:

- Bubbles and crashes: The intricate trading behavior of speculators, and in particular their reliance on technical and fundamental trading signals, creates significant bubbles and crashes. As can be seen in the top left panel of Figure 5, for instance, the stock market is overvalued up to around period 250 and then enters a significant bear market. While technical trading tends to drive stock prices away from their fundamental value, fundamental trading exercises a long-run mean reversion pressure.
- Excess volatility: Since the fundamental value of the simulated stock market is constant, we have to regard all stock price changes as excessive. Clearly, once stock prices mirror their fundamental value, there is no need for further stock market adjustments. However, speculators constantly receive new trading signals, which translate into new speculative orders and prompt the market maker to quote new stock prices, as visible in the left panels of Figure 5.
- Serially uncorrelated returns: Due to speculators' heterogeneous trading behavior – each speculator obtains her own individual trading signals, either from private market research or from following complex (algorithmic) trading systems – the path of simulated stock prices closely resembles a random walk, implying that (log) price changes are serially uncorrelated.
- Fat-tailed return distributions: Occasionally, however, we observe a breakdown of speculators' heterogeneity. For instance, salient price patterns may result in panic-induced herding behavior, leading to a spontaneous synchronization of speculators' trading behavior. Moreover, certain price signals may be hard-wired into speculators' complex (algorithmic) trading system, producing coordinated buying or selling behavior. One such example occurs shortly after period 250. As evident from the bottom left panel of Figure 5, the stock market decreases by more than 12 percent. The bottom right panel of Figure 5 illustrates that this event is associated with a strong correlation between speculators' trading signals.[9]
- Volatility clustering: If volatility picks up, speculators extract stronger trading signals out

[9] Note that a high correlation between speculators' trading behavior does not always lead to a strong stock price change. For this to be the case, speculators have to coordinate on a significant trading signal.

of past price movements. Since this leads to more forceful trading behavior, volatility may remain high. Moreover, speculators may overreact to their trading signals in periods of heightened volatility since they are agitated and thus classify their trading signals as relatively important. Such behavior lends volatility outbursts persistency. In fact, note that in periods when speculators' trading intensity is high (top right panel of Figure 5), the variability of stock prices also tends to be high (bottom left panel of Figure 5).[10]

******* Figure 5 about here *******

5 Circuit breakers

Understanding the functioning of stock markets is important. In particular, policymakers need to develop a sound economic knowledge of what really drives stock markets if they plan to implement new regulatory measures. Since our model is able to replicate a number of important stylized facts of stock markets, we may use it as an artificial laboratory to study the effects of regulatory policy measures. In this paper, we explore whether policymakers may stabilize the dynamics of stock markets by implementing circuit breakers.[11] Circuit breakers (trading halts) automatically interrupt the trading process for a given period of time when price changes are about to exceed a pre-specified limit. Policymakers hope that, by interrupting an overheated market, speculators are given time to cool off and reassess market conditions, enabling the trading process to resume in a more orderly manner after the interruption. Following the stock market crash of 1987, circuit breakers were widely implemented and are now in practice in many leading stock markets around the world. See Kim and Yang (2004) and Sifat and Mohamad (2019) for surveys.

Here we follow Westerhoff (2003, 2006, 2008) and implement circuit breakers as follows.

---

[10] Note that speculators' trading intensity (variance) may remain high for extended periods of time, thereby producing lasting volatility outbreaks, while their coordination (correlation) spikes only occasionally, forming the base for rare but extreme returns. We discuss this aspect in more detail in Appendix A.2.

[11] As pointed out by an anonymous referee, it might also be worthwhile to use our model to study the effects of margin requirements, leverage cycles and short-selling constraints. For inspiring work in this direction, see, for instance, Poledna et al. (2014), Aymanns et al. (2016) and Sng et al. (2020). Aymanns et al. (2018) and Westerhoff and Franke (2018) discuss in more detail how policymakers may use models with heterogeneous interacting agents as test beds to evaluate the effectiveness of regulatory policies.

Let parameter s stand for the maximum allowed log price change for a given trading period. Then the market maker's price adjustment rule turns into

$$P_{t+1} = \begin{cases} P_t + s & if \quad a\sum_{i=1}^{N} D_{t,i} > s \\ P_t + a\sum_{i=1}^{N} D_{t,i} & if \quad -s < a\sum_{i=1}^{N} D_{t,i} < s. \\ P_t - s & if \quad -s < a\sum_{i=1}^{N} D_{t,i} \end{cases} \tag{12}$$

If policymakers set $s = 0.05$, for instance, then the market maker has to interrupt the trading process when the log price is about to either increase or decrease by more than 5 percent. The stock market reopens in the next trading period, i.e. there are no further transactions in a period when trading has been interrupted. For simplicity, we assume that all orders that have not been executed are deleted.

Figure 6 depicts a number of possible effects of circuit breakers. The top panels show the evolution of stock prices and returns for $s = 0.05$. For comparability, the simulation run is based on the same random seed as the first simulation run in Figure 3 (top panels, marked blue). First of all, circuit breakers manage to limit extreme returns to 5 percent. However, there are further important effects. The blue lines in the bottom panels of Figure 6 report the stock market's distortion, defined as $dis = \frac{1}{T}\sum_{t=1}^{T}|P_t - F|$, and volatility, defined as $vol = \frac{1}{T}\sum_{t=1}^{T}|P_t - P_{t-1}|$, for $0 < s < 0.1$. The sample length is set to $T = 100{,}000$ observations and parameter s is increased in 25 discrete steps. As circuit breakers become more restrictive, both volatility and distortion decline. In the extreme case of $s = 0$, volatility is completely eliminated. If we furthermore assume that the initial value of the stock price is identical to its fundamental value, then circuit breakers also suppress the emergence of any kind of distortion.

Let us briefly explain how circuit breakers affect the model's stock market dynamics. Obviously, circuit breakers have an immediate direct effect: if policymakers set $s = 0.05$, for instance, there will be no stock price change larger than 5 percent. Importantly, however, there are also indirect effects that amplify the direct effect. First, circuit breakers naturally reduce the strength of speculators' technical trading signals by preventing sharp stock price changes. Technically, this effect originates from Equation (5). Second, circuit breakers reduce speculators' trading intensity (variance) by reducing the stock market's volatility, as can be concluded from Equations (6) and (7). Third, circuit breakers prevent (or at least deter) speculators from displaying panic-induced herding behavior and/or from coordinating on certain salient price patterns that are hard-wired into their complex (algorithmic) trading systems, as is evident from Equations (8) and (9).

******* Figure 6 about here *******

However, Fama (1989) argues that stock markets are efficient and thus warns that circuit breakers may only lead to a delayed price discovery and to a spillover of volatility. Here, volatility spillover means that a stock market that hits its upper or lower price boundary in the current trading period will experience greater volatility in the next trading period, since the necessary price adjustment has not yet been fulfilled. Our model allows us to address this issue, at least partially, by assuming that the stock market's fundamental value is not constant, but evolves in the form of a random walk. Accordingly, we specify the stock market's log fundamental value by

$$F_t = F_{t-1} + n_t, \tag{13}$$

where the fundamental shocks n_t that hit the stock market are normally distributed with mean zero and constant standard deviation σ^F. The blue, green and red lines depicted in the bottom lines of panels of Figure 6 are computed on the basis of $\sigma^F = 0$, $\sigma^F = 0.006$ and $\sigma^F = 0.012$. As reported in Section 3, the standard deviations of actual and simulated stock markets returns hover around 0.012. Assuming that the stock market's excess volatility is given by a factor of two (Shiller 2015), a reasonable guess for the stock market's fundamental volatility may be given by $\sigma^F = 0.006$. In order to push our analysis to the limit, we also explore the case $\sigma^F = 0.012$.

One important finding of our simulations is that circuit breakers may reduce the stock market's volatility, independently of its fundamental volatility. Another important finding of our simulations is that circuit breakers may increase the stock market's distortion if they are too restrictive. To put it differently, stock markets apparently need some price flexibility, though not a perfect price flexibility. The reason behind this outcome is that circuit breakers prevent technical and fundamental orders. If the fundamental value evolves randomly, at least some fundamental orders are needed for the stock price to be able to track its fundamental value. However, even for $\sigma^F = 0.012$, at least a mild reduction of the stock market's volatility and distortion is possible. Fundamental values are presumably less volatile than implied by $\sigma^F = 0.012$ and thus circuit breakers seem to be a useful tool for policymakers to stabilize stock markets. In this sense, our results contradict the hypothesis of a delayed price discovery process and a volatility spillover, as put forward by Fama (1989). Interestingly, the results presented in Westerhoff (2003, 2006, 2008) are quite similar to ours, despite resting on different stock market models. See also Yeh and Yang (2010, 2013) and Jacob Leal and Napoletano (2019) for more work in this direction.

6 Conclusions

Galbraiht (1994), Kindleberger and Aliber (2011) and Shiller (2015) emphatically stress that the boom-bust nature of stock markets as well as their excessively volatile behavior and tendency to produce occasionally very large price changes may be quite harmful to the real economy. In this paper, we therefore develop a simple agent-based computational model that may help us to foster our understanding of the functioning of stock markets. Within our model, stock prices adjust with respect to the excess demand of speculators, who, in turn, derive their trading signals either from private market research or from applying complex (algorithmic) trading systems. Our modeling strategy is inspired by the work of Gode and Sunder (1993), Cont and Bouchaud (2000), Iori (2002) and Alfi et al. (2009) in the sense that we use a rather minimalistic approach to represent speculators' trading behavior. In particular, we formalize speculators' orders via multivariate normally distributed random variables, which allows us to acknowledge speculators' use of technical and fundamental analysis and to condition the intensity and correlation of their trading activities on the stock market's past behavior.

Despite the simplicity of our approach, simulations reveal that our model is able to mimic a number of important stylized facts of stock markets and, consequently, may be deemed to be validated. One crucial model insight is that we may regard stock markets as self-exciting systems. If volatility picks up, speculators trade more aggressively, an outcome that keeps volatility high. Moreover, certain salient price patterns may prompt complex (algorithmic) trading systems to trigger correlated trading signals or may result in panic-induced herding behavior, yielding extreme price changes. Put differently, stock markets display a life of their own and their dynamics contains a larger endogenous component that policymakers may seek to influence. In fact, simulations reveal that policymakers may stabilize the dynamics of stock markets by implementing circuit breakers.

We conclude our paper by pointing out a few avenues for future research. The simplicity of our model allows for a number of straightforward model extensions. For instance, one may try to endogenize the number of (active) speculators, e.g. by considering interactions between different stock markets. Alternatively, one may consider that the correlation of speculators' trading signals does not depend on a single, deterministic condition, but on multiple conditions, possibly time-varying and containing stochastic elements. Although our model contains a larger number of parameters, it might be interesting to try to estimate it. The method of simulated moments seems to us to be quite appropriate for such an endeavor. We hope that our paper stimulates more work in this important and exciting research direction.

Appendix A: Robustness analysis

The robustness analysis we carry out in this appendix consists of two parts. In Appendix A.1, we first conduct a Monte Carlo study to demonstrate that the simulation runs presented in the main body of our paper may in fact be deemed as representative simulation runs. In Appendix A.2, we then conduct a sensitivity analysis to explain in more detail how certain building blocks of our model may affect its dynamics.

Appendix A.1: Monte Carlo study

Our Monte Carlo study rests on 5,000 simulation runs with 10,000 observations each, generated with the parameter setting introduced in Section 3 and different random seeds. Based on these simulations, Figure 7 shows probability density functions for volatility, distortion, the tail index at the 5 percent level, the autocorrelation coefficient of raw returns at lag 1 and the autocorrelation coefficients of absolute returns at lag 5 and at lag 95, respectively. Using these summary statistics (moments), we seek to capture a number of important stylized facts of stock markets, as discussed in Sections 3 and 4.

Our measure of volatility is defied as in Section 5, i.e. $vol = \frac{1}{T}\sum_{t=1}^{T}|P_t - P_{t-1}|$. As can be seen from the top left panel of Figure 7, our volatility estimates hover around a value of about 0.0082. Further computations reveal that 90 percent of the volatility estimates are located in the range 0.0080 and 0.0096. To put these numbers into perspective, note that the volatility estimate for the DAX, at 0.0093, fits nicely into this interval. The top right panel of Figure 7 portrays the probability density function of the simulated stock markets' distortion, defined as $dis = \frac{1}{T}\sum_{t=1}^{T}|P_t - F|$. Apparently, the average mispricing of simulated stock markets is usually above 10 percent, and can easily increase to as much as 30 percent or more. While we cannot compute the distortion for the time series discussed in Section 3, we remark that Schmitt and Westerhoff (2017b) report that the distortion of the S&P500 between 1871 and 2015 was about 30 percent.

The center left panel of Figure 7 depicts the probability density function of our estimates of the tail index (at the 5 percent level). The median estimate is 3.55, while the 90 percent confidence interval ranges from 3.2 to 3.88. According to Lux and Ausloos (2002), the tail indices for most financial market data scatter between 3 and 4. In this sense, our simple agent-based computational model is able to replicate the fat-tail property of stock market returns (though Gopikrishnan et al. 1999 and Plearou et al. 1999 stress that the tail indices of major stock markets are somewhat closer to 3). The center right panel of Figure 7 reveals that the estimated autocorrelation coefficients of raw returns at lag 1 are near zero. To be more precise, 90 percent of the estimated autocorrelation coefficients fall into the interval -0.03 and 0.03, with a median estimate of about 0.01, implying that the paths of simulated stock prices are indeed close to random walks.

The bottom two panels show probability density functions for the autocorrelation coefficients of absolute returns at lag 5 and lag 95, respectively, demonstrating our model's ability to generate volatility clustering and long memory effects. For instance, 90 percent of the estimated autocorrelation coefficients of absolute returns at lag 5 are between 0.7 and 0.22, while more than 95 percent of the estimated autocorrelation coefficients of absolute returns at lag 95 are still larger than 0.04. Hence, the volatility outbursts produced by our model are quite persistent.

******* Figure 7 about here *******

Appendix A.2: Sensitivity analysis

Finally, we outline how certain building blocks of our model may affect its dynamics. For convenience, the top panels of Figure 8 show simulated stock prices and the corresponding return dynamics for the full model, using the same parameter setting and random seed as in the top panels of Figure 3. As demonstrated above, our model is able to replicate key stylized facts of stock markets, in particular fat-tailed return distributions and volatility clustering. The center panels of Figure 8 report the dynamics of our model when its coordination mechanism is switched off (achieved by setting $\rho_t = f^l = 0.0006$). Apparently, the model is still able to produce lasting volatility outbursts, yet its ability to generated extreme returns diminishes. The bottom panels of Figure 8 present the dynamics of the model when the trading intensity mechanism is switched off (we now fix $\sigma_t^2 = 0.000003$).[12] Obviously, our model is able to generate extreme returns, yet its ability to produce lasting volatility outbursts is basically gone. More precisely, the 90 percent confidence intervals of simulated autocorrelation coefficients of absolute returns at lag 5 and at lag 95 are 0.16 and 0.21 and 0.03 and 0.09 for the model without the coordination mechanism and 0.00 and 0.04 and -0.02 and 0.02 without the trading intensity mechanism. Moreover, the 90 percent confidence intervals for the tail index (at the 5 percent level) are 3.73 and 4.59 for the model without the coordination mechanism and 3.26 and 3.78 without the trading intensity mechanism. To conclude, our simple agent-based computational model is only able to match the stylized facts of stock markets when the coordination and the trading intensity mechanism act together.

******* Figure 8 about here *******

References

Alfi, V., Cristelli, M., Pietronero, L. and Zaccaria, A. (2009): Minimal agent based model for financial markets I. European Physical Journal B, 67, 385-397.

Anufriev, M., Bao, T. and Tuinstra, J. (2016): Microfoundations for switching behavior in heterogeneous agent models: an experiment. Journal of Economic Behavior and Organization, 129, 74-99.

Arthur, B., Holland, J., LeBaron, B., Palmer, R. and Tayler, P. (1997): Asset pricing under endogenous expectations in an artificial stock market. In: Arthur, B., Durlauf, S. and Lane, D. (eds.): The economy as an evolving complex system II. Addison-Wesley, Reading, 15-44.

Aymanns, C., Farmer, D., Kleinnijenhuis, A. and Wetzer, T. (2018): Models of financial stability and their application in stress tests. In: Hommes, C. and LeBaron, B. (eds.):

[12] Our model is also able to generate extreme returns for lower values of $\sigma_t^2 = 0.000003$. However, we found that this number matches actual tail indices quite well.

Handbook of computational economics: heterogeneous agent modeling. North-Holland, Amsterdam, 329-391.

Aymanns, C., Caccioli, F., Farmer, D. and Tan, V. (2016): Taming the Basel leverage cycle. Journal of Financial Stability, 27, 263-277.

Bertschinger, N. and Mozzhorin, I. (2020): Bayesian estimation and likelihood-based comparison of agent-based volatility models. Journal of Economic Interaction and Coordination, in press.

Beja, A. and Goldman, M. (1980): On the dynamic behaviour of prices in disequilibrium. Journal of Finance, 34, 235-247.

Black, F. (1986): Noise. Journal of Finance, 41, 528-543.

Blaurock, I., Schmitt, N. and Westerhoff, F. (2018): Market entry waves and volatility out-bursts in stock markets. Journal of Economic Behavior and Organization, 153, 19-37.

Bouchaud, J.-P., Ciliberti, S., Lemperiere, Y., Majewski, A., Seager, P. and Sin Ronia, K. (2017): Black was right: price is within a factor 2 of value. Available at SSRN: https://ssrn.com/abstract=3070850.

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

Chang, I. and Stauffer, D. (1999): Fundamental judgement in Cont-Bouchaud herding model of financial fluctuations. Physica A, 264, 294-298.

Chen, S.-H. and Yeh, C.-H. (2001): Evolving traders and the business school with genetic programming: a new architecture of the agent-based artificial stock market. Journal of Economic Dynamics and Control, 25, 363-393.

Chiarella, C. (1992): The dynamics of speculative behavior. Annals of Operations Research, 37, 101-123.

Chiarella, C. and Iori, G. (2002): A simulation analysis of the microstructure of double auction markets. Quantitative Finance, 2, 1-8.

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

Cont, R. and Bouchaud, J.-P. (2000): Herd behavior and aggregate fluctuations in financial markets. Macroeconomic Dynamics, 4, 170-196.

Daniels, M., Farmer, D., Gillemot, L., Iori, G. and Smith, E. (2003): Quantitative model of price diffusion and market friction based on trading as a mechanistic random process. Physical Review Letters, 90, 108102.

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.

Delli Gatti, D., Fagiolo, G., Gallegati, M., Richiardi M. and Russo, A. (2018): Agent-based models in economics: a toolkit. Cambridge University Press, Cambridge.

Demirer, R., Demos, G., Gupta, R. and Sornette, D. (2019): On the predictability of stock market bubbles: evidence from LPPLS confidence multi-scale indicators. Quantitative Finance, 19, 843-858.

Dieci, R. and He, X.-Z. (2018): Heterogeneous agent models in finance. In: Hommes, C. and LeBaron, B. (eds.): Handbook of computational economics: heterogeneous agent modeling. North-Holland, Amsterdam, 257-328.

Dieci, R., Schmitt, N. and Westerhoff, F. (2018): Interactions between stock, bond and housing markets. Journal of Economic Dynamics and Control, 91, 43-70.

Diem, C., Pichler, A., Thurner, S. (2020): What is the minimal systemic risk in financial exposure networks? Journal of Economic Dynamics and Control, 116, 103900.

Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A. and Roventini, A. (2017): Validation of agent-based models in economics and finance. In: Beisbart, C. and Saam, N. (eds.): Computer simulation validation. Springer, Berlin, 763-787.

Fama, E. (1989): Perspectives on October 1987, or, what did we learn from the crash? In: Kampuis, R. Kormendi, R. and Watson, J. (eds.): Black Monday and the future of financial markets. Irwin, Homewood, 71-82.

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

Farmer, D., Patelli, P. and Zovko, I. (2005a): The predictive power of zero intelligence in financial markets. Proceedings of the National Academy of Sciences, 102, 2254-2259.

Farmer, D., Gillemot, l., Iori, G., Krishnamurthy, S., Smith, E. and Daniels, M. (2005b): A random order placement model of price formation in the continuous double auction. In: Blume, L. and Durlauf, S. (eds.): The economy as an evolving complex system, III: current perspectives and future directions. Oxford University Press, Oxford, 133-173.

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.

Franke, R. and Westerhoff, F. (2016): Why a simple herding model may generate the stylized facts of daily returns: explanation and estimation. Journal of Economic Interaction and Coordination, 11, 1-34.

Galbraiht, J. K. (1994): A short history of financial suphoria. Penguin Books, London.

Gode, D. and Sunder, S. (1993): Allocative efficiency of markets with zero-intelligence traders: market as a partial substitute for individual rationality. Journal of Political Economy, 101, 119-137.

Gode, D. and Sunder, S. (1997): What makes markets allocationally efficient? Quarterly Journal of Economics, 112, 603-630.

Gomber, P. and Zimmermann, K. (2018): Algorithmic trading in practice. In: Chen, S.-H., Kaboudan, M. and Du, Y.-R. (eds.): The Oxford handbook on computational economics and finance, Oxford University Press, Oxford, 311-332.

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

Greenwald, B. and Stein, J. (1991): Transactional risk, market crashes, and the role of circuit breakers. Journal of Business 64, 443-462.

Gopikrishnan, P., Plerou, V., Amaral, L., Meyer, M. and Stanley, E. (1999): Scaling of the distributions of fluctuations of financial market indices. Physical Revue E, 60, 5305-5316.

Guerini, M. and Moneta, A. (2017): A method for agent-based models validation. Journal of Economic Dynamics and Control, 82, 125-141.

Harris, L. (1998): Circuit breakers and program trading limits: what have we learned? In: Litan, R. and Santomero, A. (eds.): Brookings-Wharton papers on financial services. Brookings Institution Press, Washington, 17-64.

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

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

Iori, G. (2002): A microsimulation of traders activity in the stock market: the role of heterogeneity, agents' interactions and trade frictions. Journal of Economic Behavior and Organization, 49, 269-285.

Iori, G. and Porter, J. (2018): Agent-based modeling for financial markets. In: Chen, S.-H., Kaboudan, M. and Du, Y.-R. (eds.): The Oxford handbook of computational economics and finance. Oxford University Press, Oxford, 635-666.

Jacob Leal, S., Napoletano, M., Roventini, A. and Fagiolo, G. (2016): Rock around the clock: an agent-based model of low- and high-frequency trading. Journal of Evolutionary Economics, 26, 49-76

Jacob Leal, S. and Napoletano, M. (2019): Market stability vs. market resilience: regulatory policies experiments in an agent-based model with low- and high-frequency trading. Journal of Economic Behavior and Organization, 157, 15-41.

Keynes, J.M. (1936): The general theory of employment, interest, and money. Harcourt, Brace and Company, New York.

Kim, Y. and Yang, J. (2004): What makes circuit breakers attractive to financial markets? A survey. Financial Markets, Institutions and Instruments, 13, 109-146.

Kindleberger, C. and Aliber, R. (2011): Manias, panics, and crashes: a history of financial crises. Wiley, New Jersey.

Kukacka, J. and Kristoufek, L. (2020): Do 'complex' financial models really lead to complex dynamics? Agent-based models and multifractality. Journal of Economic Dynamics and Control, 113, 103855.

Ladley, D. (2012): Zero intelligence in economics and finance. Knowledge Engineering Review, 27, 273-286.

Ladley, D., Lensberg, T., Palczewski, J. and Schenk-Hoppe, K. R. (2015): Fragmentation and stability of markets. Journal of Economic Behavior and Organization, 119, 466-481.

Ladley, D. (2020): The high frequency trade off between speed and sophistication. Journal of Economic Dynamics and Control, 116, 103912.

Lamperti, F., Roventini, A., and Sani, A. (2018): Agent-based model calibration using machine learning surrogates. Journal of Economic Dynamics and Control, 90, 366-389.

LeBaron, B., Arthur, B. and Palmer, R. (1999): Time series properties of an artificial stock market. Journal of Economic Dynamics and Control, 23, 1487-1516.

Lo, A., Mamaysky, H. and Wang, J. (2000): Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. Journal of Finance, 4, 1705-1765.

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

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 Zwinkels, R. (2018): Empirical validation of agent-based models. In: Hommes, C. and LeBaron, B. (eds.): Handbook of computational economics: heterogeneous agent modeling. North-Holland, Amsterdam, 437-482.

Majewski, A., Ciliberti, S. and Bouchaud, J.-P. (2020): Co-existence of trend and value in financial markets: estimating an extended Chiarella model. Journal of Economic Dynamics and Control, 112, 103791.

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

Manzan, S. and Westerhoff, F. (2005): Representativeness of news and exchange rate dynamics. Journal of Economic Dynamics and Control, 29, 677-689.

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.

Palmer, R., Arthur, B., Holland, J., LeBaron, B. and Tayler, P. (1994): Artificial economic life: a simple model of a stock market. Physica D, 75, 264-274.

Platt, D. (2020): A comparison of economic agent-based model calibration methods. Journal of Economic Dynamics and Control, 113, 103859.

Plerou, V., Gopikrishnan, P., Amaral, L., Meyer, M. and Stanley, E. (1999): Scaling of the distribution of price fluctuations of individual companies. Physical Revue E, 60, 6519-6529.

Poledna, S., Thurner, S., Farmer, D. and Geanakoplos, J. (2014): Leverage-induced systemic risk under Basle II and other credit risk policies. Journal of Banking and Finance, 42, 199-212.

Raberto, M., Cincotti, S., Focardi, S. and Marchesi, M. (2001): Agent-based simulation of a financial market. Physica A, 299, 319-327.

Schmitt, N. (2020): Heterogeneous expectations and asset price dynamics. Macroeconomic Dynamics, forthcoming.

Schmitt, N. and Westerhoff, F. (2017a): Heterogeneity, spontaneous coordination and extreme events within large-scale and small-scale agent-based financial market models. Journal of Evolutionary Economics, 27, 1041-1070.

Schmitt, N. and Westerhoff, F. (2017b): Herding behaviour and volatility clustering in financial markets. Quantitative Finance, 17, 1187-1203.

Schmitt, N. and Westerhoff, F. (2017c): On the bimodality of the distribution of the S&P 500's distortion: empirical evidence and theoretical explanations. Journal of Economic Dynamics and Control, 80, 34-53.

Schmitt, N., Tramontana, F. and Westerhoff, F. (2020): Nonlinear asset-price dynamics and stabilization policies. Nonlinear Dynamics, in press.

Shiller, R. (2015): Irrational exuberance. Princeton University Press, Princeton.

Sifat, I. and Mohamad, A. (2019): Circuit breakers as market stability levers: a survey of research, praxis, and challenges. International Journal of Finance and Economics, 24, 1130-1169.

Sng, H., Zhang, Y. and Zheng, H. (2020): Margin trade, short sales and financial stability. Journal of Economic Interaction and Coordination, 15, 673-702.

Stanek, F. and Kukacka, J. (2018): The impact of the Tobin tax in a heterogeneous agent model of the foreign exchange market. Computational Economics**,** 51, 856-892.

Stauffer, D. and Penna, T. (1998): Crossover in the Cont-Bouchaud percolation model for market fluctuations. Physica A, 256, 284.

Stauffer, D. and Sornette, D. (1999): Self-organized percolation model for stock market fluctuation. Physica A, 271, 496-506.

Stauffer, D. and Jan, N. (2000): Sharp peaks in the percolation model for the stock markets. Physica A, 277, 215-219.

Vassiliadis, V and Dounias, G. (2018): Algorithmic trading based on biologically inspired algorithms. In: Chen, S.-H., Kaboudan, M. and Du, Y.-R. (eds.): The Oxford handbook on computational economics and finance. Oxford University Press, Oxford, 295-310.

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

Westerhoff, F. (2006): Technical analysis based on price-volume signals and the power of trading breaks. International Journal of Theoretical and Applied Finance, 9, 227-244.

Westerhoff, F. (2008): The use of agent-based financial market models to test the effectiveness of regulatory policies. Jahrbücher für Nationalökonomie und Statistik (Journal of Economics and Statistics), 228, 195-227.

Westerhoff, F. and Franke, R. (2018): Agent-based models for policy analysis: two illustrative examples. In: Chen, S.-H., Kaboudan, M. and Du, Y.-R. (eds.): The Oxford handbook of computational economics and finance. Oxford University Press, Oxford, 520-558.

Westphal, R. and Sornette, D. (2020): Market impact and performance of arbitrageurs of financial bubbles in an agent-based model. Journal of Economic Behavior and Organization, 171, 1-23.

Xing, G. and Ladley, D. (2019): Noise trading and market stability. Available at SSRN: https://ssrn.com/abstract=3415141

Yeh, C.-H. and Yang, C.-Y. (2010): Examining the effectiveness of price limits in an artificial stock market. Journal of Economic Dynamics and Control, 34, 2089-2108.

Yeh, C.-H. and Yang, C.-Y. (2013): Do price limits hurt the market? Journal of Economic Interaction and Coordination, 8, 125-153.

Zeeman, E.C. (1974): On the unstable behaviour of stock exchanges. Journal of Mathematical Economics, 1, 39-49.

Zhang, Q., Sornette, D. and Zhang, H. (2019): Anticipating critical transitions of the housing market: new evidence from China. European Journal of Finance, 25, 1251-1276.

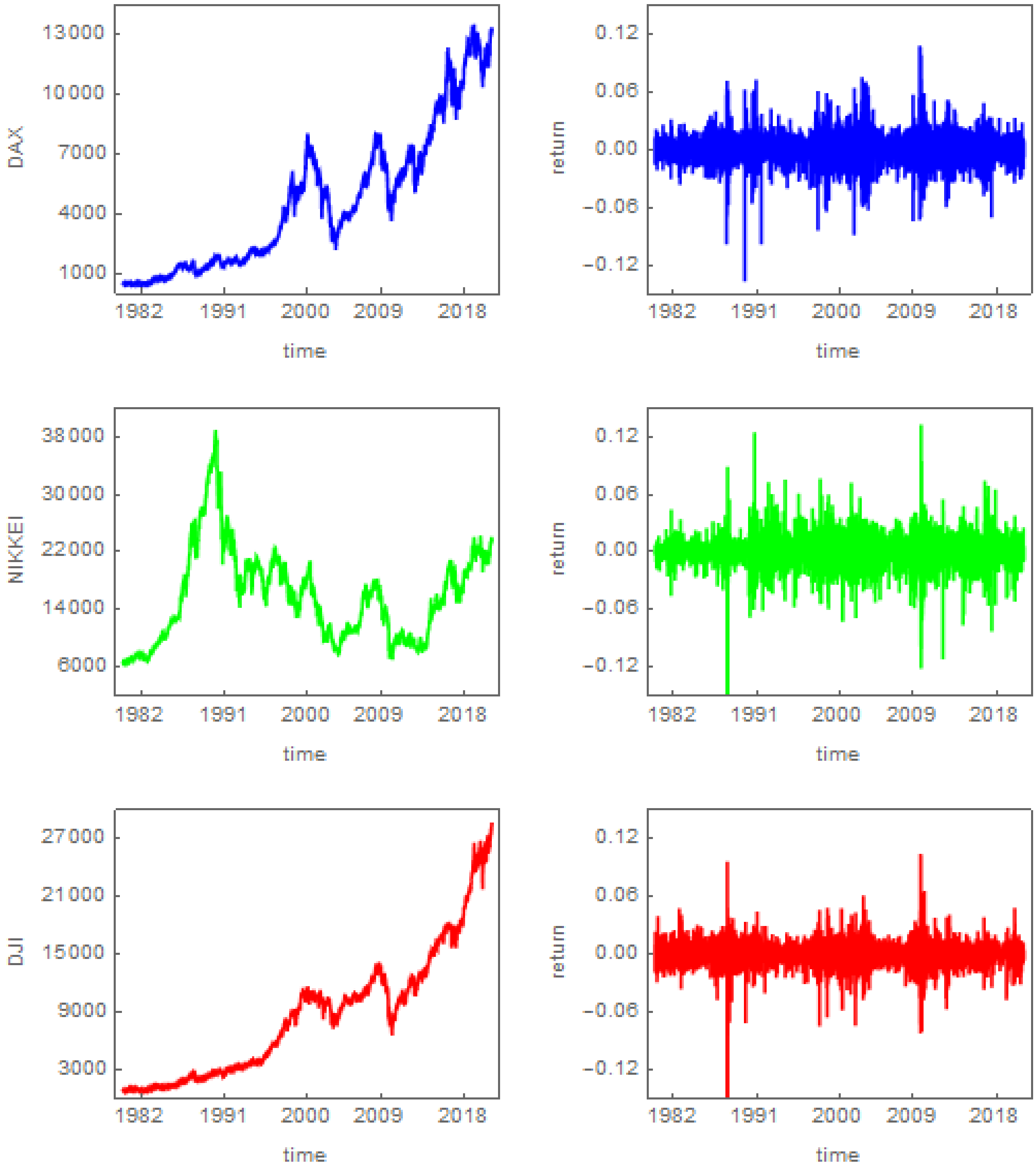


Figure 1: Time series dynamics of actual stock markets. The left panels show the evolution of the DAX, the NIKKEI and the DJI from 1980 to 2019, comprising about 10,000 daily observations. The right panels show the corresponding return dynamics.

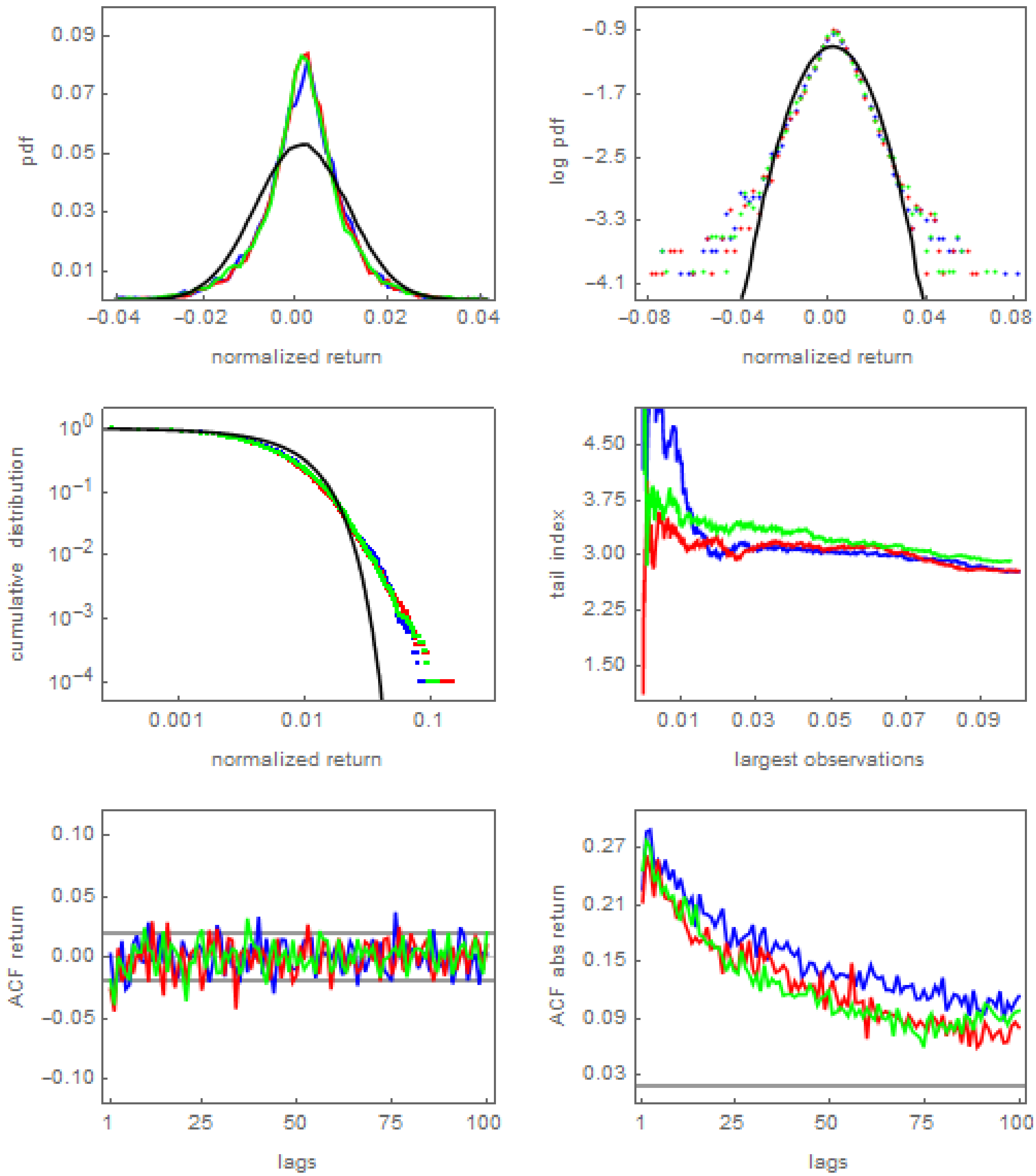


Figure 2: Distributional and correlation properties of actual stock markets. The panels show a number of distributional and correlation properties of the DAX, the NIKKEI and the DJI. The same data set and color coding as in Figure 1.

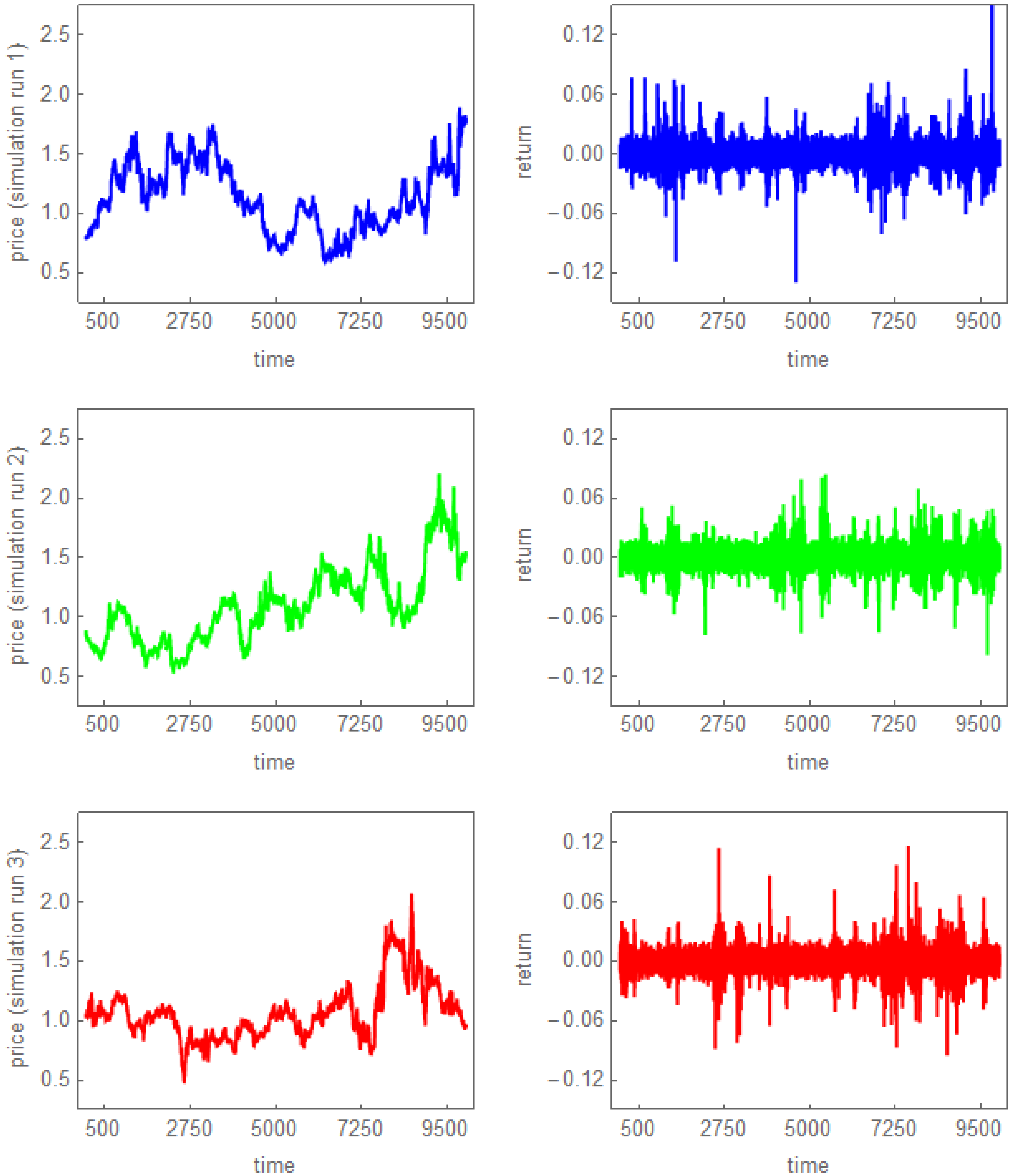


Figure 3: Time series dynamics of simulated stock markets. The left panels show the evolution of three stock market simulations, comprising 10,000 daily observations. The right panels show the corresponding return dynamics. Parameter setting as in Section 3.

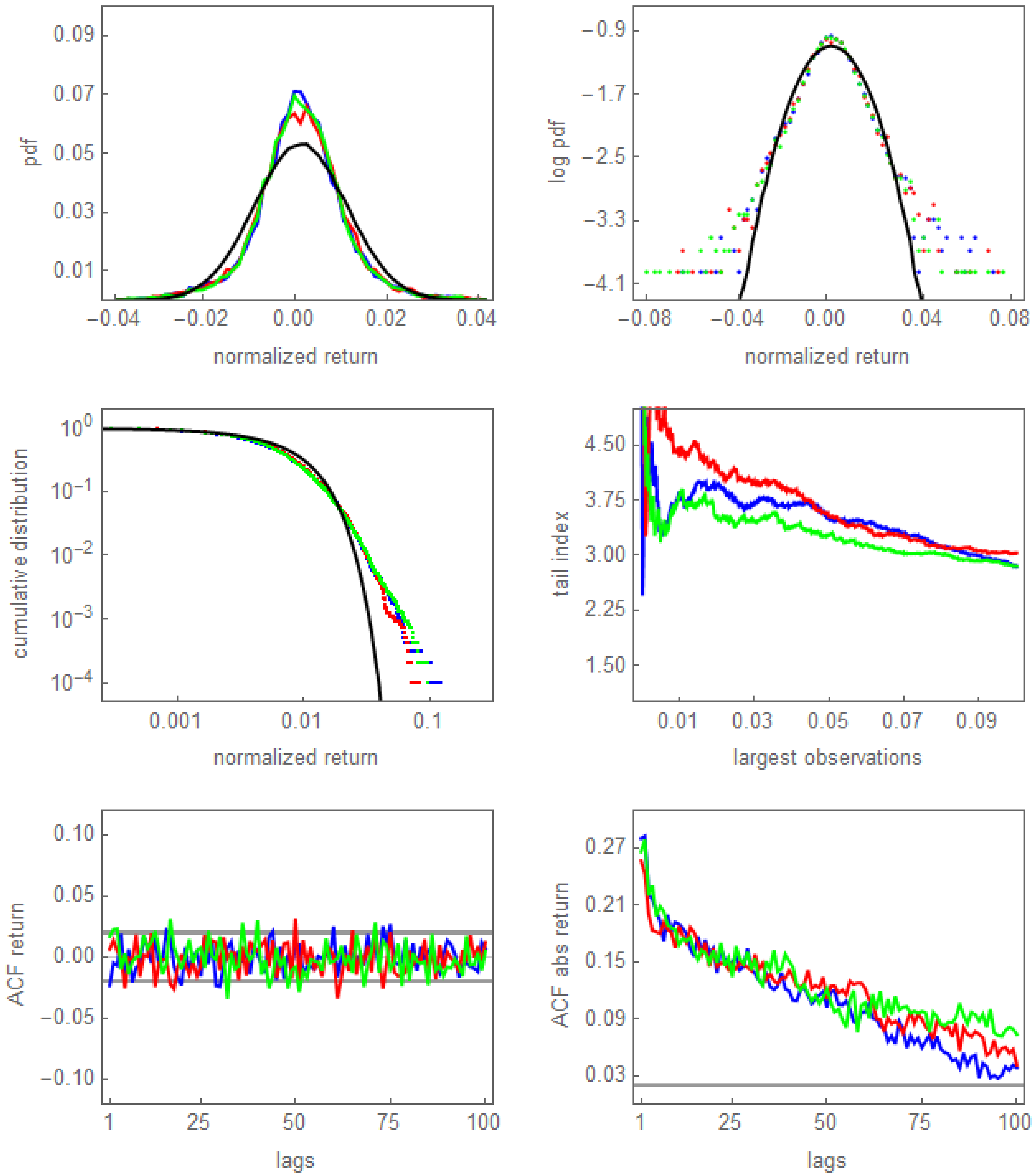


Figure 4: Distributional and correlation properties of simulated stock markets. The panels show a number of distributional and correlation properties of three representative stock market simulations. The same data set and color coding as in Figure 3.

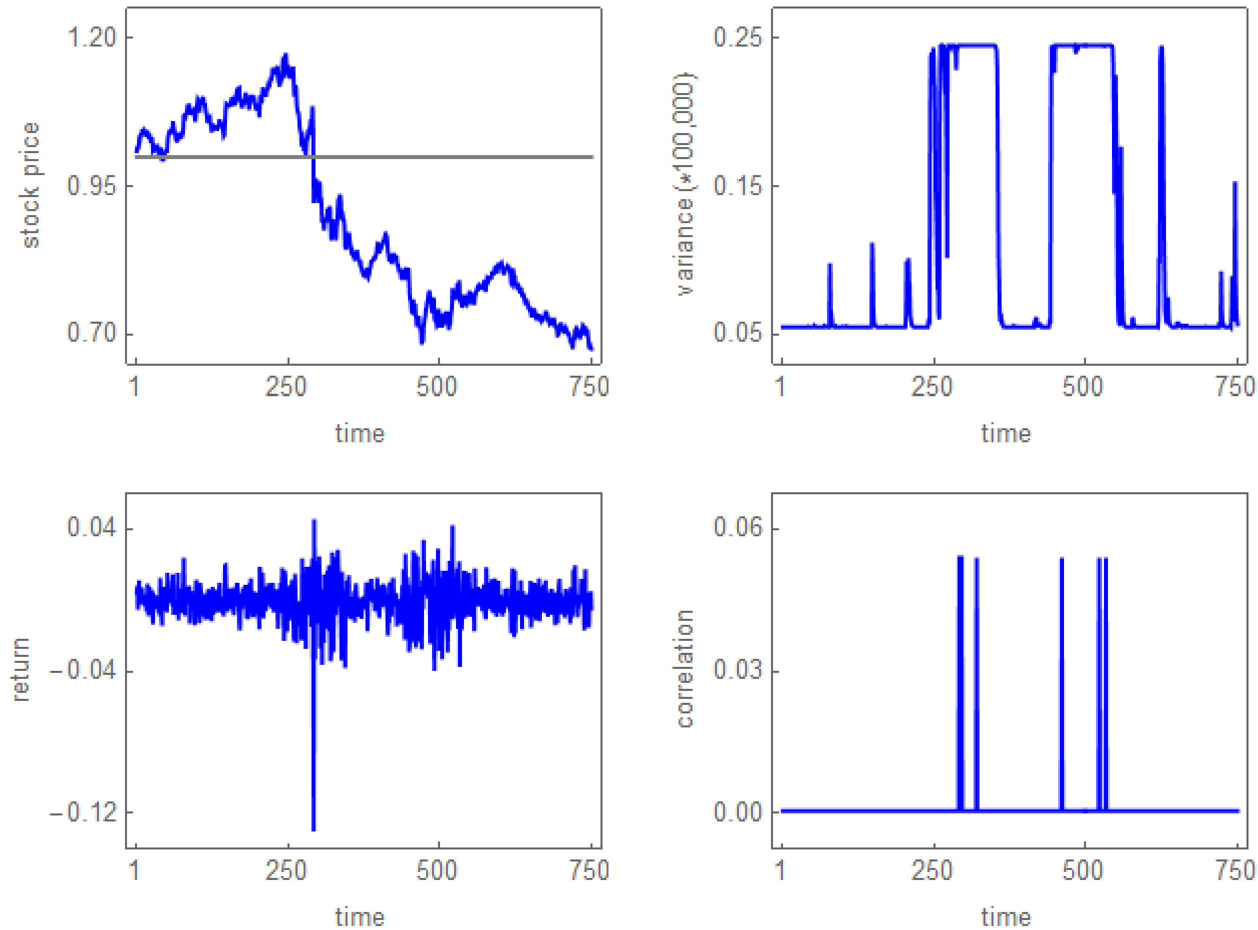


Figure 5: Functioning of model. The left panels show the evolution of simulated stock prices and returns while the right panels show speculators' trading intensity (variance) and their coordination (correlation). Extract of the first simulation run, as depicted in Figure 3, ranging from period 4351 to 5100.

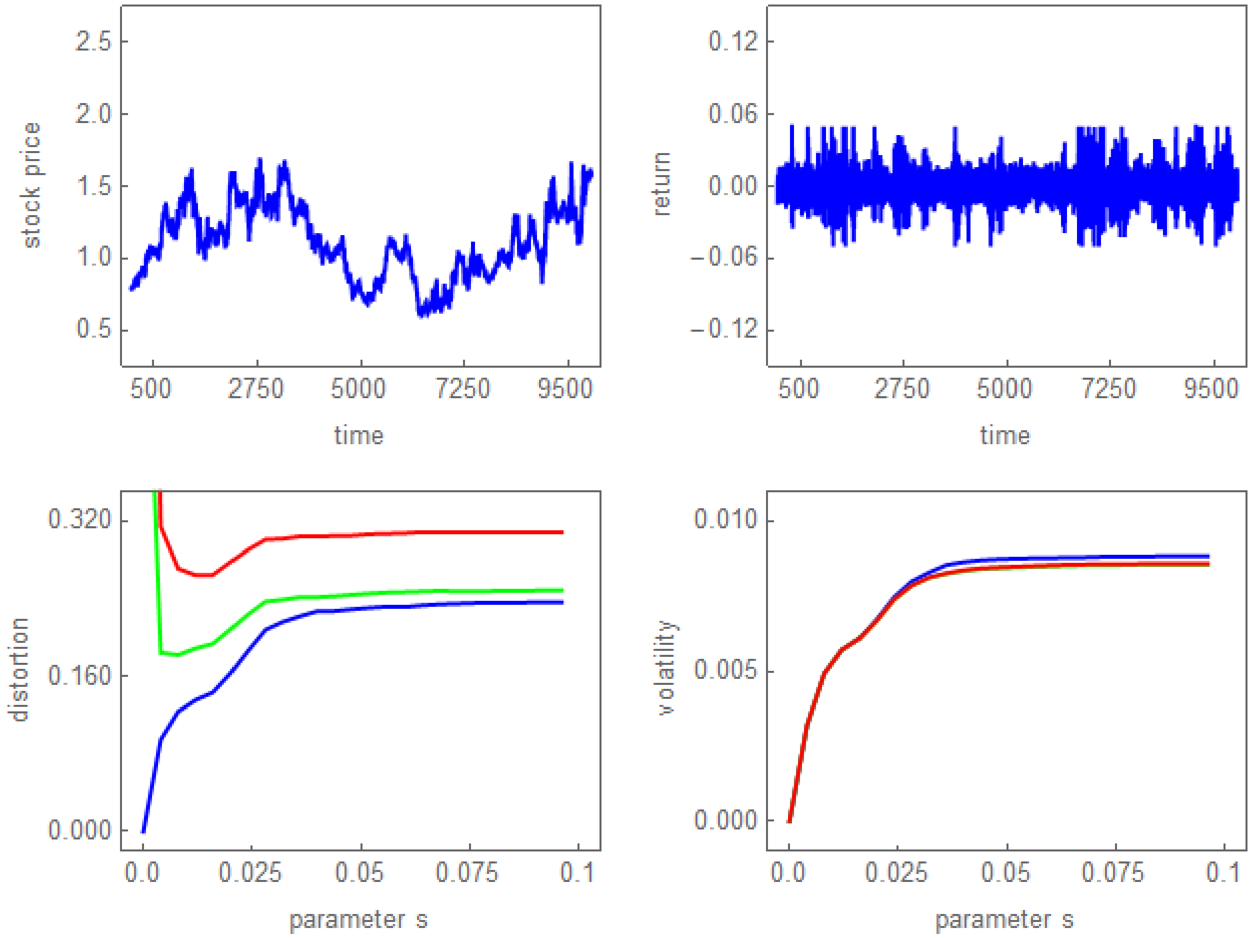


Figure 6: Effects of circuit breakers. The top panels show the evolution of stock prices and returns for $s = 0.05$, respectively. The bottom panels show the stock market's distortion and volatility for $0 < s < 0.1$. Blue, green and red lines are based on $\sigma^F = 0$, $\sigma^F = 0.006$ and $\sigma^F = 0.012$, respectively. Remaining parameters as in Section 3.

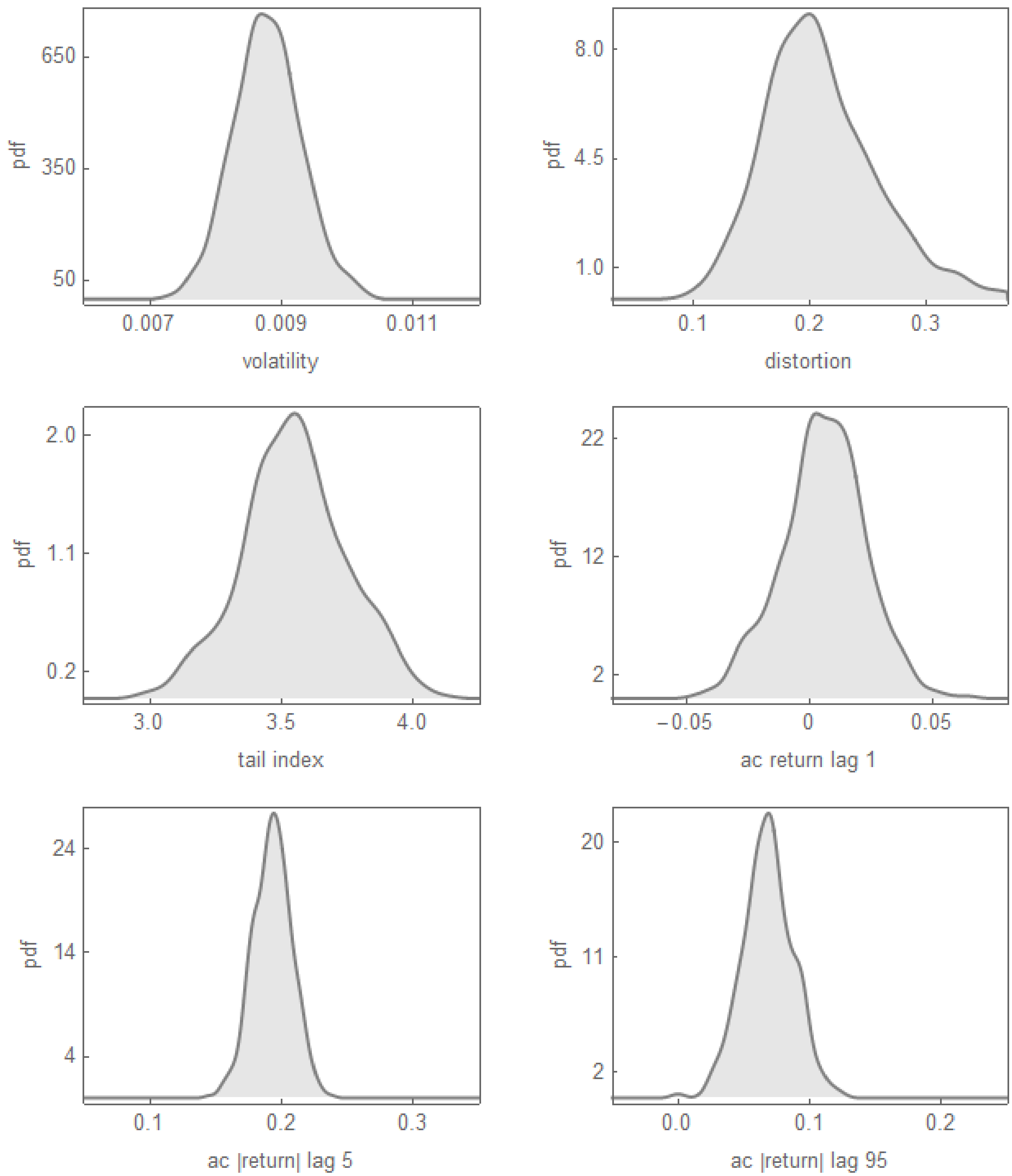


Figure 7: Monte Carlo study. The panels show probability density functions for volatility, distortion, the tail index, the autocorrelation coefficient of raw returns at lag 1 and the autocorrelation coefficients of absolute returns at lag 5 and lag 95, respectively, based on 5,000 simulation runs with 10,000 observations each. Parameter setting as in Section 3.

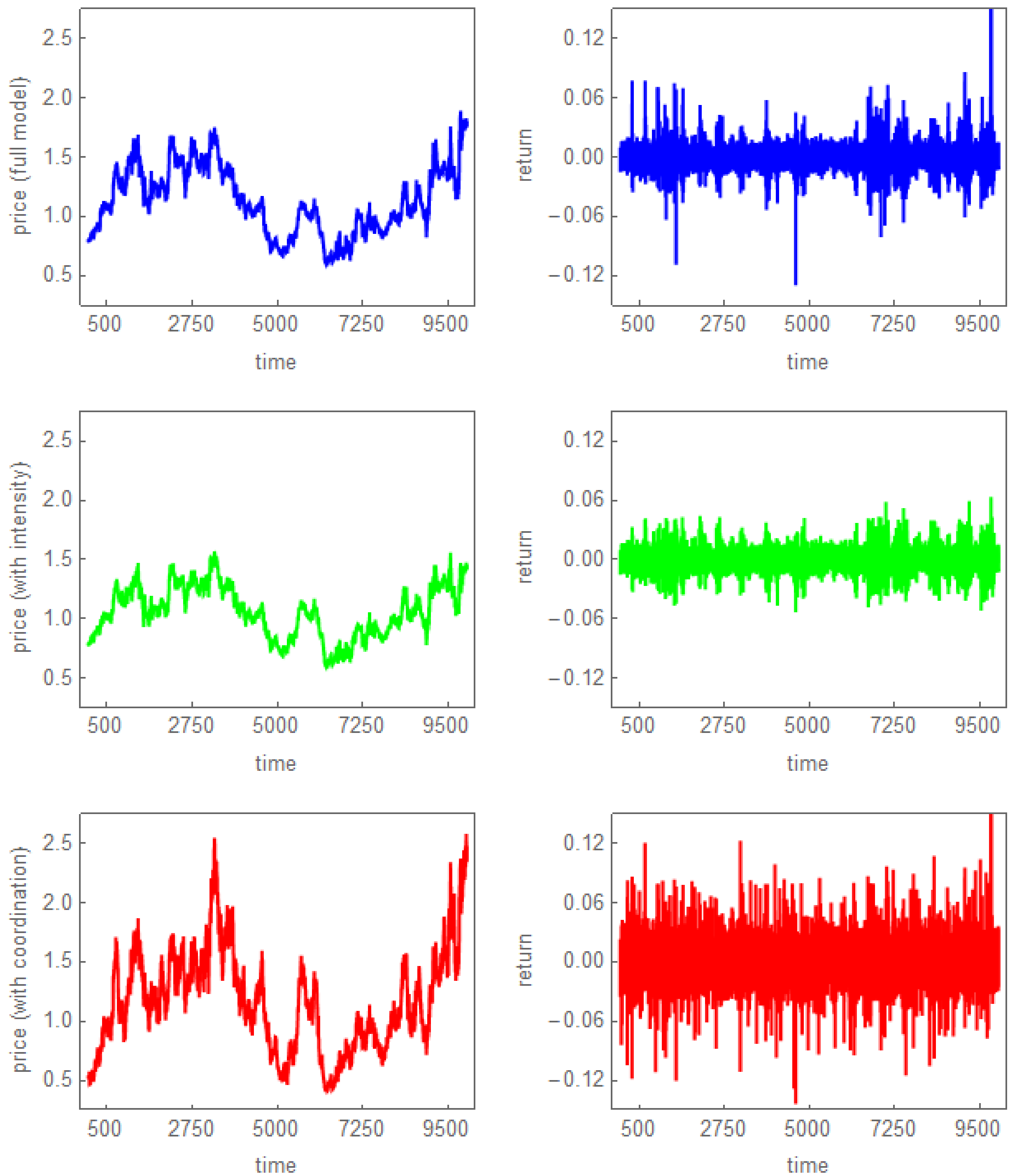


Figure 8: Sensitivity analysis. The left and right panels show simulated stock prices and return dynamics for 10,000 time steps, respectively. Top: full model. Center: model without coordination mechanism, i.e. $\rho_t = 0.0006$. Bottom: model without trading intensity mechanism, i.e. $\sigma_t^2 = 0.000003$. Remaining parameters as in Section 3.

BERG Working Paper Series (most recent publications)

128 Ivonne **Blaurock**, Noemi **Schmitt** and Frank **Westerhoff**, Market entry waves and volatility outbursts in stock markets, August 2017

129 Christoph **Laica**, Arne **Lauber** and Marco **Sahm**, Sequential Round-Robin Tournaments with Multiple Prizes, September 2017

130 Joep **Lustenhouwer** and Kostas **Mavromatis**, Fiscal Consolidations and Finite Planning Horizons, December 2017

131 Cars **Hommes** and Joep **Lustenhouwer**, Managing Unanchored, Heterogeneous Expectations and Liquidity Traps, December 2017

132 Cars **Hommes**, Joep **Lustenhouwer** and Kostas **Mavromatis**, Fiscal Consolidations and Heterogeneous Expectations, December 2017

133 Roberto **Dieci**, Noemi **Schmitt** and Frank **Westerhoff**, Interactions between stock, bond and housing markets, January 2018

134 Noemi **Schmitt**, Heterogeneous expectations and asset price dynamics, January 2018

135 Carolin **Martin** and Frank **Westerhoff**, Regulating speculative housing markets via public housing construction programs: Insights from a heterogeneous agent model, May 2018

136 Roberto **Dieci**, Noemi **Schmitt** and Frank **Westerhoff**, Steady states, stability and bifurcations in multi-asset market models, July 2018

137 Steffen **Ahrens**, Joep **Lustenhouwer** and Michele **Tettamanzi**, The Stabilizing Role of Forward Guidance: A Macro Experiment, September 2018

138 Joep **Lustenhouwer**, Fiscal Stimulus in an Expectation Driven Liquidity Trap, September 2018

139 Tim **Hagenhoff**, An aggregate welfare optimizing interest rate rule under heterogeneous expectations, October 2018

140 Johanna Sophie **Quis**, Anika **Bela** and Guido **Heineck**, Preschoolers' self-regulation, skill differentials, and early educational outcomes, December 2018

141 Tomasz **Makarewicz,** Traders, forecasters and financial instability: A model of individual learning of anchor-and-adjustment heuristics, January 2019

142 Carolin **Martin**, Noemi **Schmitt** and Frank **Westerhoff**, Housing markets, expectation formation and interest rates, January 2019

143 Marc P. **Saur**, Markus G. **Schlatterer** and Stefanie Y. **Schmitt**, Horizontal product differentiation with limited attentive consumers, January 2019

144 Tim **Hagenhoff** and Joep **Lustenhouwer**, The Rationality Bias, February 2019

145 Philipp **Mundt** and Ilfan **Oh**, Asymmetric competition, risk, and return distribution, February 2019

146 Ilfan **Oh**, Autonomy of Profit Rate Distribution and Its Dynamics from Firm Size Measures: A Statistical Equilibrium Approach, February 2019

147 Philipp **Mundt**, Simone **Alfarano** and Mishael **Milakovic**, Exploiting ergodicity in forecasts of corporate profitability, March 2019

148 Christian R. **Proaño** and Benjamin **Lojak**, Animal Spirits, Risk Premia and Monetary Policy at the Zero Lower Bound, March 2019

149 Christian R. **Proaño**, Juan Carlos **Peña** and Thomas **Saalfeld**, Inequality, Macroeconomic Performance and Political Polarization: An Empirical Analysis, March 2019

150 Maria Daniela **Araujo P.**, Measuring the Effect of Competitive Teacher Recruitment on Student Achievement: Evidence from Ecuador, April 2019

151 Noemi **Schmitt** and Frank **Westerhoff**, Trend followers, contrarians and fundamentalists: explaining the dynamics of financial markets, May 2019

152 Yoshiyuki **Arata** and Philipp **Mundt**, Topology and formation of production input interlinkages: evidence from Japanese microdata, June 2019

153 Benjamin **Lojak**, Tomasz **Makarewicz** and Christian R. **Proaño**, Low Interest Rates, Bank's Search-for-Yield Behavior and Financial Portfolio Management, October 2019

154 Christoph **March**, The Behavioral Economics of Artificial Intelligence: Lessons from Experiments with Computer Players, November 2019

155 Christoph **March** and Marco **Sahm**, The Perks of Being in the Smaller Team: Incentives in Overlapping Contests, December 2019

156 Carolin **Martin**, Noemi **Schmitt** and Frank **Westerhoff**, Heterogeneous expectations, housing bubbles and tax policy, February 2020

157 Christian R. **Proaño**, Juan Carlos **Peña** and Thomas **Saalfeld**, Inequality, Macroeconomic Performance and Political Polarization: A Panel Analysis of 20 Advanced Democracies, June 2020

158 Naira **Kotb** and Christian R. **Proaño**, Capital-Constrained Loan Creation, Stock Markets and Monetary Policy in a Behavioral New Keynesian Model, July 2020

159 Stefanie Y. **Schmitt** and Markus G. **Schlatterer**, Poverty and Limited Attention, July 2020

160 Noemi **Schmitt**, Ivonne **Schwartz** and Frank **Westerhoff**, Heterogeneous speculators and stock market dynamics: a simple agent-based computational model, July 2020