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Abstract: In many economic models (including many models from economics of climate change) the agents make decisions solely on the basis of 'objective' information (e.g., the market price level). However, a number of alternative modeling frameworks have been developed, where individual economic agents, when making decisions, take into account the observed behavior of other economic agents. One of pioneering contributions to this research area was the Kirman's 'ant model' (Kirman, 1993). While initially the model was applied to describing the collective behavior of social insects (ants), later it was extensively used for describing the 'herding behavior' in economic systems. Particularly, 'herding behavior' of traders is in the core of a model of a financial market proposed by Alfarano et al. (2008). In the model a system of individual traders of three types is considered: fundamentalist traders, optimistic noise traders, and pessimistic noise traders. The decision-making of fundamentalists buying and selling the units of an asset is based on 'objective' information solely (i.e. on the perceived 'fundamental' value of the asset price). The total number of all noise traders is constant in time; however, the number of optimists taken separately (and therefore the number of pessimists) fluctuates, and the dynamics of fluctuations are described by a modified stochastic Kirman's ant model. In our previous study (Lebedeva and Kovalevsky, 2015) we modified the model by Alfarano et al. (2008) outlined above by going beyond a simplifying approximation of instantaneous market clearing and exploring the model with the full dynamic version of Walrasian price adjustment law. In the present paper we first report new results of numerical and analytical studies of the model modified in such a way. Then, we make one more modification, from now on treating the 'fundamental' value of the asset price not as a constant, but rather as a stochastic variable affected by exogenous shocks. Particularly, these shocks, temporarily reducing the 'fundamental' price of the asset, might be caused by climate-related natural hazards. These modifications of the model allow us studying the interplay of external (climate-related) and internal (herding-related) stochasticity on the financial market jointly affecting the asset price dynamics.

Keywords*:* climate change; natural hazard; financial market; herding behaviour; price dynamics.

1 INTRODUCTION

Agent based models (ABM) are playing more and more prominent role in economic modeling in general (Farmer and Foley, 2009; Li et al., 2013) and climate/environmental economics in particular (Farmer et al., 2015; Filatova et al., 2011; Wolf et al., 2013). ABM and other types of models where the economic system is described as a (usually very large) population of individual economic agents pave the way to describing many important features of real-world economic decision making, particularly the effects related to 'herding behavior' (Kirman, 1993; Alfarano et al., 2008). Herding behavior can emerge where individual economic agents, when making decisions, take into account not only the 'objective' information (e.g., the market price level), but also the observed behavior of other economic agents. As pointed out in a number of recent publications, the appropriate description of herding behavior in economic systems is relevant for studying many climate/environmental-related issues like food security (Timmer, 2012), households' decision making in energy use practices (Frederiks et al., 2015), and financial shocks originating from ecological imbalances (Schoenmaker et al., 2015).

In the present paper we develop a model of financial market with herding behavior of traders and exogenous shocks caused by climate-related natural hazards.

The rest of the paper is organized as follows. We depart from the model developed and studied in detail by Alfarano et al. (2008) (outlined in Sec. 2 below) and make two important modifications: (i) we first go beyond a simplifying approximation of instantaneous market clearing adopted by Alfarano et al. (2008) and explore the model with the full dynamic version of Walrasian price adjustment law (Sec. 3); (ii) we then include in the model exogenous shocks caused by climate-related natural hazards affecting the ‘fundamental’ value of the asset price at the financial market (Sec. 4). Sec. 5 concludes.

2 A MODEL OF FINANCIAL MARKET WITH HERDING BEHAVIOUR OF TRADERS

Following the model presented by Alfarano et al. (2008), we consider the financial market (on which the only asset is traded) as a system of traders of two types: ‘fundamentalists’ and ‘chartists’ (or noise traders).

Fundamentalists (whose number is constant and equal to N_{f}) buy (sell) the asset if its current price $p(t)$ is below (above) their perceived fundamental value p_{f} of the price (that is assumed to be constant in Secs. 2-3). The average trading volume for one fundamentalist is T_{f}.

Noise traders are divided into optimists and pessimists, who expect the price $p(t)$ to increase or decrease in the near future, respectively. Optimists (pessimists) are assumed to buy (sell) a certain number T_{c} of additional units of the asset. The total number of noise traders is constant and equal to N. However, the number of optimists $n(t)$ (and hence the number of pessimists equal to $N-n(t)$) fluctuates in time (see the notes on modeling the noise traders’ herding behavior leading to these fluctuations of $n(t)$ below).

It is convenient to define the *population configuration* of noise traders $x(t)$ as

$$x(t)=\frac{2n(t)}{N}-1\,. \tag{1}$$

As, in general, $n(t)$ may vary within the limits $0\le n(t)\le N$, $x(t)$ varies within the limits $-1\le x(t)\le 1$. The boundary case $x(t)=1$ corresponds to the situation when all noise traders are optimists, while in the opposite case $x(t)=-1$ all noise traders are pessimists.

Putting this altogether, Alfarano et al. (2008) derive the stochastic ordinary differential equation (ODE) for asset price dynamics based on a standard Walrasian price adjustment mechanism:

$$\frac{1}{p}\frac{dp}{dt}=\beta\left[N_{\mathrm{f}}T_{\mathrm{f}}\ln\left(\frac{p_{\mathrm{f}}}{p}\right)+NT_{\mathrm{c}}x\right] \tag{2}$$

where β is a price adjustment speed.

Regarding the dynamics of $x(t)$ (driven, according to (1), by the dynamics of $n(t)$), Alfarano et al. (2008) assume that it is affected by herding behavior of noise traders that can be described by a seminal Kirman’s ant model (Kirman, 1993). According to this model, the dynamics of population of noise traders can be modeled by a Markov process with transition rates

$$\pi(n\rightarrow n+1)=(N-n)\left(a+\bar{b}\,\frac{n}{N}\right), \tag{3}$$

$$\pi(n\rightarrow n-1)=n\left(a+\bar{b}\,\frac{N-n}{N}\right) \tag{4}$$

where $a = \mathrm{const}$, $\bar{b} = \mathrm{const}$. Of course the third option is that n remains unchanged at the next incremental time step; increasing/decreasing of n by more than unity at one step can be neglected in the analysis.

Alfarano et al. (2008) also consider the following modified form of the Markov process (3)-(4):

$$\pi(n \to n+1) = (N-n)(a+bn), \quad (5)$$

$$\pi(n \to n-1) = n(a + b(N-n)) \quad (6)$$

where $a = \mathrm{const}$, $b = \mathrm{const}$, and provide an in-depth analysis of how replacing $\bar{b}/N$ in (3)-(4) by b in (5)-(6) fundamentally changes the scaling properties of the model.

3 NUMERICAL AND ANALYTICAL RESULTS

Alfarano et al. (2008) provide the detailed analysis of the model outlined in the previous section, however, their results are obtained within a simplifying assumption of instantaneous market clearing only (i.e. it is assumed that in (2) $\beta \to +\infty$). In this limiting case the model is tractable to an extent that many elegant results are derived by Alfarano et al. (2008) in closed analytical form.

In our previous study (Lebedeva and Kovalevsky, 2015) we have gone beyond this approximation and explored the model with the full dynamic version of Walrasian price adjustment law (i.e. for finite β). However, our analysis of the general case of finite price adjustment speed so far was purely numerical. At the same time, some results can be obtained in closed analytical form for finite β as well. Particularly, in the present section we will derive an exact formula for price variance in the general case.

To do this, we first rewrite (2) in terms of logarithms of prices, introducing the notations

$$z(t) = \ln p(t), \quad (7)$$

$$z_{\mathrm{f}} = \ln p_{\mathrm{f}}, \quad (8)$$

and denote for brevity

$$\xi = \frac{NT_{\mathrm{c}}}{N_{\mathrm{f}} T_{\mathrm{f}}}, \quad (9)$$

$$\lambda = \beta N_{\mathrm{f}} T_{\mathrm{f}}. \quad (10)$$

Then the stochastic price dynamics ODE (2) takes the form

$$\dot{z} = \lambda[z_{\mathrm{f}} - z + \xi x]. \quad (11)$$

Finally, denote

$$\mathrm{v}(t) = z(t) - z_{\mathrm{f}}, \quad (12)$$

$$\mathrm{f}(t) = \xi x(t). \quad (13)$$

We thus come to the Langevin equation (A.1) described in the Appendix:

$$\dot{\mathrm{v}}(t) = -\lambda[\mathrm{v}(t) - \mathrm{f}(t)] \quad (14)$$

As follows from definition (13) of $\mathrm{f}(t)$ and the analysis performed by Alfarano et al. (2008), the random force $\mathrm{f}(t)$ has zero mean, and the autocorrelation function $B(t-t') = \langle \mathrm{f}(t)\mathrm{f}(t') \rangle$ that in the Langevin approximation for the stochastic process driving $x(t)$ itself can be approximated as[1]

[1] This follows from Eqs. (15) and (19) in (Alfarano et al., 2008).

$$B(\tau) = \frac{\xi^2}{2\varepsilon + 1} \exp(-2a\tau) \quad (15)$$

where

$$\varepsilon = Na / \overline{b} \quad (16)$$

in case of the Markov process (3)-(4) [the standard Kirman's ant model], and

$$\varepsilon = a / b \quad (17)$$

for the Markov process (5)-(6) [the modified Kirman's ant model].

Therefore, we can directly apply the formula (A.7) from the Appendix that yields the variance of $\mathrm{v}(t)$ in the stationary regime:

$$D_\infty = \left\langle \mathrm{v}^2(t) \right\rangle = \frac{\xi^2}{2\varepsilon + 1} \cdot \frac{\lambda}{\lambda + 2a}. \quad (18)$$

It follows immediately from (10) that finite (infinite) β corresponds to finite (infinite) λ, respectively. Obviously, the second factor in the r.h.s. of (18) is strictly less than unity for any finite value of λ (and hence of β), approaching its asymptotic value of unity only in the limit $\lambda \to +\infty$ ($\beta \to +\infty$). Therefore, we come to a conclusion that in a more realistic model with finite speeds of price adjustment β the variance of the price is reduced as compared to the case of instantaneous market clearing ($\beta = +\infty$) considered in detail by Alfarano et al. (2008).

The realizations of all random processes appearing in the financial market model described in Secs. 2-3 can be conveniently generated in Vensim ® DSS software.[2]

Particularly, in Figure 1a the dynamics of population configuration of noise traders $x(t)$ generated by the standard Kirman's ant model (3)-(4) is shown. For illustrative purposes, the total number of noise traders is chosen to be very small ($N = 20$), hence the pronounced discreteness of the random process presented in Figure 1.

Figure 1b, in its turn, presents the stochastic price dynamics modeled by (2) driven exactly by the same realization of the random process $x(t)$ as presented in Figure 1a. Unlike in (Alfarano et al., 2008), the price adjustment speed β is finite here.

4 MODELING EXOGENOUS CLIMATE-RELATED SHOCKS

So far, we were assuming that the fundamental value p_{f} of the asset price is a constant. In the present section we adopt a more general treatment, implying instead that p_{f} might be affected by exogenous shocks and therefore vary in time. In the context of our study, we assume that these random exogenous shocks are caused by climate-related natural hazards that temporarily reduce p_{f}. The latter, however, tends to ultimately restore to its 'unperturbed' value until the next random shock comes.

Different ways of including the climate- and weather-related stochasticity in economic models are reported in the literature. For instance, Weber (2004), when developing a stochastic version of the MADIAM model,[3] introduces the climate-related stochasticity in the form of a Poisson point process with Rayleigh amplitude distributions. Hallegatte et al. (2007) introduce in the previously developed non-equilibrium model of economic dynamics NEDyM (Hallegatte et al., 2008) stochastic climate-

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[2] The Vensim ® DSS software is developed by Ventana Systems, Inc. (http://vensim.com/).
[3] (Weber, 2004, Chapter 7). MADIAM is an acronym for a Multi-Actor Dynamic Integrated Assessment Model. The deterministic version of MADIAM as presented in (Weber, 2004) is also described in detail in the subsequent paper (Weber et al., 2005).

related damages caused by Large-scale Extreme Weather events (LEWE) as a random process with a Weibull distribution of economic losses from any single extreme event (see also (Hallegatte and Ghil, 2008)).

In our stylized generalization of the model (2) we assume that exogenous shocks caused by climate-related natural hazards make z_{f} appearing in (8) a random process of the form

$$z_{\mathrm{f}}(t) = z_{\mathrm{f0}} - \frac{\Delta_0}{2}\left(1 + \varsigma(t)\right) \tag{19}$$

where Δ_0 is a constant and $\varsigma(t)$ is a telegraph process switching between two states $\varsigma = +1$ and $\varsigma = -1$ at random points of time defined by a Poisson point process of the intensity μ. This means that $z_{\mathrm{f}}(t)$ is switching between two states $z_{\mathrm{f}} = z_{\mathrm{f0}}$ and $z_{\mathrm{f}} = z_{\mathrm{f0}} - \Delta_0$, hence $p_{\mathrm{f}}(t)$ is switching between two states $p_{\mathrm{f}} = p_{\mathrm{f0}}$ and $p_{\mathrm{f}} = p_{\mathrm{f0}} \exp(-\Delta_0)$ where $p_{\mathrm{f0}} = \exp(z_{\mathrm{f0}})$ (see (8)). As follows from (Klyatskin, 2003), this telegraph process has zero mean and the autocorrelation function[4]

$$\left\langle \varsigma(t)\varsigma(t')\right\rangle = \exp\left(-2\mu\left|t - t'\right|\right). \tag{20}$$

This means that (11) can now be generalized to the form

$$\dot{z} = \lambda\left[z_{\mathrm{f}}^* - z + \mathrm{f}_1\right] \tag{21}$$

where

$$z_{\mathrm{f}}^* = z_{\mathrm{f0}} - \frac{\Delta_0}{2}, \tag{22}$$

and

$$\mathrm{f}_1(t) = \mathrm{f}(t) - \frac{\Delta_0}{2}\varsigma(t) = \xi x(t) - \frac{\Delta_0}{2}\varsigma(t). \tag{23}$$

As two random processes $x(t)$ and $\varsigma(t)$ appearing in the r.h.s. of (23) are independent, the autocorrelation function of the resultant random process $B_1\left(t - t'\right) = \left\langle \mathrm{f}_1(t)\mathrm{f}_1(t')\right\rangle$ is merely a sum of autocorrelation functions of these two random processes. According to (15), (20), and (23),

$$B_1(\tau) = \frac{\xi^2}{2\varepsilon + 1}\exp(-2a\tau) + \frac{\Delta_0^2}{4}\exp(-2\mu\tau). \tag{24}$$

Note that despite the random processes $x(t)$ and $\varsigma(t)$ are fundamentally different, the autocorrelation functions in the r.h.s. of (24) are of very similar (exponential) structure.

If we now introduce

$$\mathrm{v}_1(t) = z(t) - z_{\mathrm{f}}^*, \tag{25}$$

analogously to (12), and then rewrite (21) in the form

$$\dot{\mathrm{v}}_1(t) = -\lambda\left[\mathrm{v}_1(t) - \mathrm{f}_1(t)\right], \tag{26}$$

we easily get (analogously to (18)) the variance of $\mathrm{v}_1(t)$ in the stationary regime:

$$D_{1\infty} = \left\langle \mathrm{v}_1^2(t)\right\rangle = \frac{\xi^2}{2\varepsilon + 1}\cdot\frac{\lambda}{\lambda + 2a} + \frac{\Delta_0^2}{4}\cdot\frac{\lambda}{\lambda + 2\mu}. \tag{27}$$

Therefore, climate-related external shocks in our model *reduce* the mean fundamental value of the price (see (22)), but, at the same time, *increase* the variance of the price $p(t)$ (see (27)).

[4] (Klyatskin, 2003, p. 134).

These results are illustrated by stochastic simulations of price dynamics presented in Figure 2. The olive stepwise line depicts the fundamental value of the price $p_{\mathrm{f}}(t)$ driven by a telegraph process as a proxy for a sequence of exogenous climate-related shocks. The blue line corresponds to the model *without* exogenous shocks, with stochasticity caused by herding behavior of noise traders solely, as described by (2) (Sec. 2 above). The red line corresponds to the model *with* exogenous climate-related shocks, as outlined in the present section. Note that the realizations of random process $x(t)$ describing the herding behavior are *the same* in both cases presented in Figure 2 (i.e. for the blue and the red line).

As clearly seen from Figure 2, at time intervals when the fundamental value of the price drops (referred to as time intervals of type 1 below), after a rapid transition period the red line differs from the blue line only by a constant scaling factor (less than unity), while at time intervals when the fundamental value of the price is restored (referred to as time intervals of type 2 below), the blue and the red line rapidly converge and then start almost coinciding. Both of these features can be easily interpreted by analyzing the properties of the model described in the Appendix. Indeed, as obvious for the previous analysis, and also from (A.3)-(A.4) (see Appendix), if the realizations of the driving random force $\mathrm{f}(t) = \xi x(t)$ are the same in both cases (with and without climate-relates shocks), at time intervals of type 1, after a rapid transition process described by the exponentially decaying deterministic term in (A.3), the logarithms of the price $p(t)$ differ only by an additive constant; hence the prices themselves differ only by a multiplicative scaling factor. At time intervals of type 2, again after a rapid transition process described by the decaying term in (A.3), the logarithms of the price $p(t)$ coincide; hence the prices themselves coincide as well.

5 CONCLUSIONS

In the present paper, we first contributed to further development of a simple model of herding behavior on a financial market initially proposed by Alfarano et al. (2008), and then included into the model exogenous stochastic climate-related external shocks affecting the fundamental value of the price of the asset. This extension of the model allowed us studying the interplay of external (climate-related) and internal (herding-related) stochasticity. Particularly, we found that when climate-related shocks are included in the modeling scheme, the mean fundamental value of the asset price is reduced, while the variance of the asset price $p(t)$ is increased.

In future work we are planning to further advance the mathematical description of climate-related shocks and their impacts on the financial market (in the present framework modeled in a very stylized way by the telegraph process – one of the simplest random processes).

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Appendix. LANGEVIN EQUATION

Following Klyatskin (2003), we consider a stochastic ODE of the form

$$\frac{d}{dt}\mathrm{v}(t) = -\lambda\left[\mathrm{v}(t) - \mathrm{f}(t)\right] \tag{A.1}$$

with the initial condition

$$\mathrm{v}(0) = \mathrm{v}_0 \tag{A.2}$$

and a stationary random force $\mathrm{f}(t)$ in the r.h.s. of (A.1) with zero mean and the autocorrelation function $\langle \mathrm{f}(t)\mathrm{f}(t') \rangle = B(t-t')$.

The solution $\mathrm{v}(t)$ of a system (A.1)-(A.2), for a particular realization of the random force $\mathrm{f}(t)$ takes the form

$$\mathrm{v}(t) = \mathrm{v}_0 \exp(-\lambda t) + \mathrm{w}(t) \tag{A.3}$$

where the stochastic term

$$\mathrm{w}(t) = \lambda \int_0^t d\tau \exp(-\lambda(t-\tau)) \mathrm{f}(t), \tag{A.4}$$

has zero mean

$$\langle \mathrm{w}(t) \rangle = 0, \tag{A.5}$$

while the dynamics of its variance $D(t) = \langle \mathrm{w}^2(t) \rangle$ is given by a formula

$$D(t) = \langle \mathrm{w}^2(t) \rangle = \lambda \int_0^t d\tau B(\tau) [\exp(-\lambda\tau) - \exp(-\lambda(2t-\tau))]. \tag{A.6}$$

Particularly, in the limit of $t \to +\infty$ we obtain from (A.6) the variance in the stationary regime[5]

$$D_\infty = \langle \mathrm{v}^2(t) \rangle = \langle \mathrm{w}^2(t) \rangle = \lambda \int_0^{+\infty} d\tau B(\tau) \exp(-\lambda\tau). \tag{A.7}$$

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[5] (Klyatskin, 2003, p. 108).

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FIGURES

a) b)

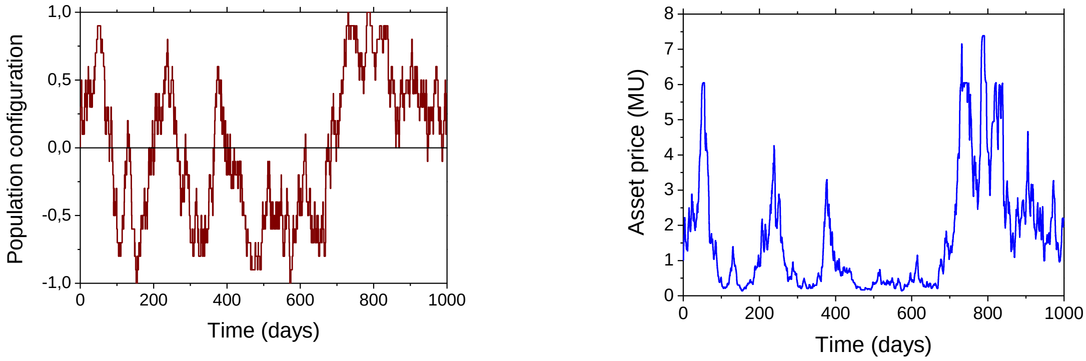

Figure 1. a) The population configuration of noise traders $x(t)$ (see (1) in Sec. 2) simulated in Vensim ® DSS software following the standard Kirman's ant model of herding behavior (3)-(4). The total number of noise traders is $N = 20$. b) The stochastic price dynamics described by (2) driven by the realization of the random process $x(t)$ presented in Figure 1a. The price adjustment speed β is finite. Monetary units (MU) are arbitrary.

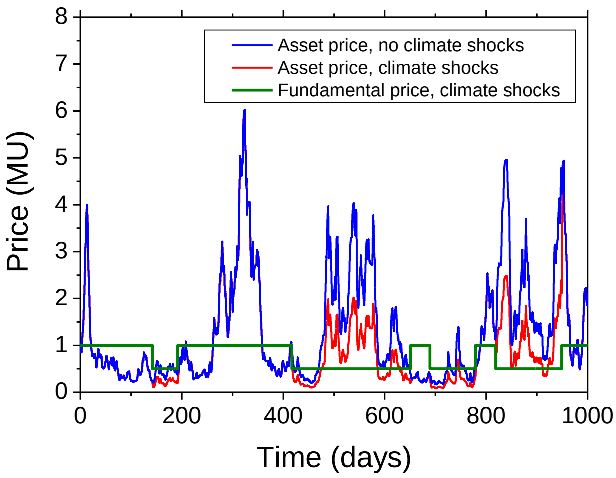

Figure 2. The stochastic price dynamics for models with (the red line) and without (the blue line) exogenous stochastic climate-related shocks affecting the fundamental value of the asset price (the olive line). See Sec. 4 for details. Monetary units (MU) are arbitrary.