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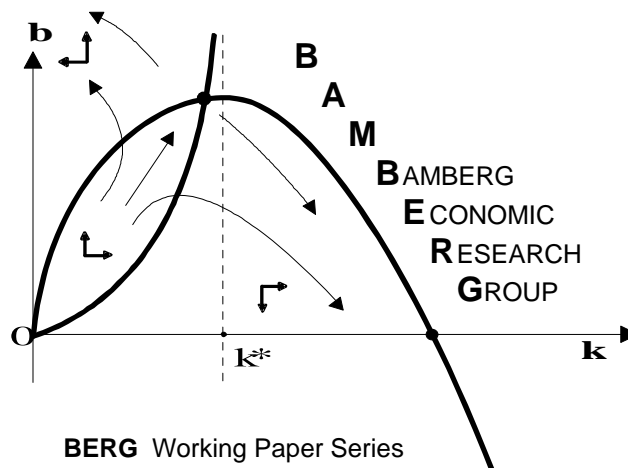
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**Agent-based models for economic policy design:
two illustrative examples**

Frank Westerhoff^{*} and Reiner Franke^{**}

Abstract

With the help of two examples, we illustrate the usefulness of agent-based models as a tool for economic policy design. In our first example, we apply a financial market model in which the order flow of speculators, relying on technical and fundamental analysis, generates intricate price dynamics. In our second example, we apply a Keynesian-type goods market model in which the investment behavior of firms, relying on extrapolative and regressive predictors, generates complex business cycles. We add a central authority to these two setups and explore the impact of simple intervention strategies on the model dynamics. Based on these experiments, we conclude that agent-based models may help us to understand how markets function and to evaluate the effectiveness of various stabilization policies.

Keywords

Agent-based models; Economic policy design;
Financial markets; Goods markets; Simulation analysis.

JEL classification

C63; D84; E32; G12.

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1 Introduction

Agent-based models have made substantial progress in various areas of economic research in recent years (for surveys see Tesfatsion and Judd 2006, Hens and Schenk-Hoppé 2009, Rosser 2009). In this contribution, we discuss the usefulness of these models for economic policy design by means of two examples. Our first example is concerned with financial markets. Here we present an agent-based financial market model in which a central authority, say a central bank, applies simple intervention rules to stabilize the evolution of prices. In our second example, we develop an agent-based goods market model to study how a central authority, say a government, may stabilize national income by adjusting its expenditure. Overall, we conclude that agent-based models may serve as artificial laboratories to study how markets function and the effects of various stabilization policies. Moreover, we also provide advice on how to design and implement such policy experiments and point out their shortcomings, drawbacks and limitations. To be able to pin down the effects of regularity policies, our survey focuses primarily on small-scale agent-based models.

Let us turn to our first example. From an economic point of view, financial markets are quite volatile and frequently display severe bubbles and crashes. Since the dynamics of financial markets may be harmful to the real economy, policy makers regularly debate about the stronger regulation of financial markets. However, it is often unclear how the implementation of policy measures such as transaction taxes, trading halts or short-selling constraints will affect the markets, especially if they have never been applied before. Fortunately, a number of agent-based financial market models (e.g. Day and Huang 1990, Kirman 1991, Chiarella 1992, de Grauwe *et al.* 1993, Lux 1995, Brock and Hommes 1998, LeBaron *et al.* 1999, Farmer and Joshi 2002, Westerhoff and Dieci 2006, He and Li 2007) exist which have improved our understanding of financial markets and which may be used to address these questions.

The dynamics of agent-based financial market models is driven by the trading behavior of heterogeneous speculators who follow simple trading strategies. As we know from many empirical studies, as summarized by Menkhoff and Taylor (2007), financial market participants rely on technical and fundamental analysis to predict the future direction of the market. Whilst technical analysis (Murphy 1999) derives trading signals from past price movements, fundamental analysis (Graham and Dodd 1951) presumes that prices will return towards their fundamental values. Note that trend-extrapolating behavior and mean-reversion behavior have also been observed in laboratory experiments, as summarized by Hommes (2011), so there is widespread empirical evidence to back the main cornerstones of these models.

Overall, technical analysis destabilizes financial markets. In periods where many speculators opt for technical analysis, strong price fluctuations and significant bubbles may be observed. In contrast, fundamental analysis lends stability to financial markets. In a market in which a sufficiently large number of speculators follow fundamental analysis, prices are relatively stable and tend to move towards fundamental values. Of course, alternating periods of turbulent and calm market dynamics may emerge if both forces act together. Since agent-based financial market models are quite powerful, they have already been used in the past as artificial laboratories to scrutinize the effects of various policy measures (see Westerhoff 2008 for an early survey).

In the current study, we use an agent-based financial market model by Franke and Westerhoff (2012). In their model, a market maker adjusts prices with respect to excess demand and speculators select between technical and fundamental trading rules to determine their orders. The speculators' choice of trading rules is endogenous and depends on predisposition effects, herding behavior and market circumstances. As it turns out, this model is quite successful at mimicking the dynamics of financial markets. Since prices adjust in this model with respect to excess demand, it is easy to add a central authority that also participates

in the trading process and, by manipulating excess demand, seeks to direct the development of prices. In particular, we explore two strategies. According to the first strategy, the central authority buys in undervalued markets and sells in overvalued markets, thus trading in the same direction in which fundamental traders usually trade. According to the second strategy, the central authority trades against past price trends and thus counters the orders of chartists. As we will see, agent-based models may help us to understand how such interventions may influence the market dynamics.

Small-scale agent-based business cycle models have also been proposed in recent years, such as those by Westerhoff (2006a), Tuinstra and Wagener (2007), Franke (2008), Branch and McGough (2009), Lines and Westerhoff (2010), de Grauwe (2010), Anufriev *et al.* (2012) and Franke (2012). Although these models are not yet as well developed as their financial market counterparts, they are already able to explain business cycle dynamics, at least to some degree. In most of these models, market participants have to form expectations, say inflation expectations or output expectations. For this task, they endogenously select between different forecasting rules (the analogy between agent-based financial market models and agent-based business cycle models will be clarified below) and it is this switching behavior that creates endogenous dynamics in these models. The use of extrapolative expectations tends to amplify business cycle fluctuations whilst the use of regressive expectations exerts a dampening effect on the dynamics. If both forces gain and lose popularity over time, intricate business cycles may emerge. We are currently observing several new exciting results with respect to the effectiveness of monetary and fiscal policy rules in this research area.

The agent-based business cycle model employed in our study is quite simple. Essentially, we have a Keynesian-type goods market model in which firms' investment expenditure depends on national income expectations. Investment expenditure increases if firms expect a boom, and vice versa. A firm forms its expectations on the basis of an

extrapolative or a regressive prediction rule, between which the firm dynamically selects with respect to predisposition effects, herding behavior and market assessments. Simulations reveal that the model is able to produce complex business cycles. We therefore study whether simple fiscal policy rules may stabilize the evolution of national income. According to one strategy, the central authority increases (decreases) its expenditure if national income is below (above) a desired target value. According to the other strategy, it increases (decreases) its expenditure if national income decreases (increases). As it turns out, agent-based business cycle models give us an idea of how these strategies may affect the dynamics.

The remainder of this paper is organized as follows. In Section 2, a simple agent-based financial market model is introduced in which a central authority applies different strategies to stabilize the price dynamics. In Section 3, a simple agent-based goods market model is proposed in which a central authority relies on different strategies to stabilize the evolution of national income. The paper closes with a summary and an outlook.

2 Financial markets

In this section, we present a simple agent-based financial market model (for surveys see Chiarella *et al.* 2009, Hommes and Wagener 2009, Lux 2009, Westerhoff 2009, Chen *et al.* 2012). Since the setup is quite stylized, it may be interpreted as a model for stock markets, commodity markets or foreign exchange markets or, more generally, as a model for speculative markets. For simplicity, however, we call it a model for financial markets. We will use this model to analyze whether a central authority has the ability to stabilize the dynamics of financial markets by applying basic intervention strategies. To this end, we introduce some statistics that allow us to measure the success or failure of these interventions and to check their viability.

2.1 A simple agent-based financial market model

The agent-based financial market model of Franke and Westerhoff (2012) serves as our workhorse. In their model, a market maker quotes prices with respect to speculative excess demand and the speculators determine their orders following a representative technical or a representative fundamental trading rule. According to the technical trading rule, prices move in trends and buying (selling) is suggested when prices increase (decrease). The fundamental trading rule predicts that prices will return towards their fundamental value. In undervalued markets, fundamental trading rules recommend buying and in overvalued markets they propose selling. In each time step, speculators have to select one of the two strategies. The choice made by speculators depends on three socio-economic principles: a predisposition towards one of the two strategies, herding behavior and an evaluation of the current market circumstances.

Since the model of Franke and Westerhoff (2012) has a remarkable ability to match some important stylized facts of financial markets, it seems reasonable to use it as an artificial laboratory to conduct a number of policy experiments. Therefore, we add a central authority to the model. The central authority seeks to stabilize the dynamics by applying simple feedback strategies. One intervention strategy aims to push the price towards a desired target value. If the target value corresponds with the fundamental value, then the central authority trades in the same direction as the fundamentalists. The other strategy seeks to counter the behavior of chartists by trading against past price trends. As reported by Neely (2005), such strategies are frequently applied by central banks in foreign exchange markets to stabilize exchange rate fluctuations. We assume that all interventions by the central authority are secret. As a result, speculators cannot strategically exploit the interventions, nor it is clear to them that the course of the price is influenced by the central authority. The latter observation is important since technical traders may otherwise lose their trust in these price signals.

Let us now turn to the formal part of the model and start with the behavior of the market maker. As usual, the market maker collects all individual orders from speculators and changes the price with respect to the resulting excess demand. Therefore, we write

$$P_{t+1} = P_t + a(NW_t^C D_t^C + NW_t^F D_t^F + D_t^A), \quad (1)$$

where P_t is the log of the price (at time step t), a is a positive price adjustment parameter, N is the total number of speculators, W_t^C is the market share of speculators following a technical trading rule, D_t^C is the order of a (single) chartist, W_t^F is the market share of speculators following a fundamental trading rule, D_t^F is the order of a (single) fundamentalist, and D_t^A is the order (intervention) of a central authority. According to (1), excess buying drives prices up and excess selling drives them down. Without loss of generality, we set the price adjustment parameter to $a = 0.01$ and normalize the population size of speculators to $N = 1$.

The orders placed by chartists and fundamentalists depend on their price expectations, given by $E_t^C[P_{t+1}]$ and $E_t^F[P_{t+1}]$, respectively. If speculators expect a price increase (decrease), they buy (sell), as indicated by the first term on the right-hand side of trading rules (2) and (3). However, the trading motives of speculators may be more complicated – which is why we add random terms to their trading rules. Jointly, this gives us

$$D_t^C = b_0^C (E_t^C[P_{t+1}] - P_t) + \varepsilon_t^C \quad (2)$$

and

$$D_t^F = b_0^F (E_t^F[P_{t+1}] - P_t) + \varepsilon_t^F, \quad (3)$$

where b_0^C and b_0^F are positive reaction parameters and $\varepsilon_t^C \sim N(0, \sigma_0^C)$ and $\varepsilon_t^F \sim N(0, \sigma_0^F)$ are normally distributed random variables with mean zero and constant standard deviation.

Chartists and fundamentalists rely on different expectation formation schemes. Since technical analysis predicts that prices move in trends, we express chartists' expectations as

$$E_t^C [P_{t+1}] = P_t + b_1^C (P_t - P_{t-1}) + \eta_t^C . \quad (4)$$

Accordingly, chartists pay attention to the most recent price trend, where b_1^C is a positive extrapolation parameter. To capture part of the variety of the many existing technical prediction rules, we add a normally distributed random variable $\eta_t^C \sim N(0, \sigma_1^C)$ with mean zero and constant standard deviation to (4).

In contrast, fundamentalists believe that prices will revert towards their fundamental values. Let P^* be the log of the fundamental value, known to all market participants. Fundamentalists' expectations are formalized as

$$E_t^F [P_{t+1}] = P_t + b_1^F (P^* - P_t) + \eta_t^F , \quad (5)$$

with $0 < b_1^F < 1$ as a mean reversion parameter. Since fundamentalists may display digressions from pure mean reversion expectations, we also add a normally distributed random variable $\eta_t^F \sim N(0, \sigma_1^F)$ with mean zero and constant standard deviation to (5).

Combining (2) and (5), and assuming that the random variables in these equations are independent, we obtain the simplified trading rules

$$D_t^C = b^C (P_t - P_{t-1}) + \delta_t^C \quad (6)$$

and

$$D_t^F = b^F (P^* - P_t) + \delta_t^F , \quad (7)$$

where $b^C = b_0^C b_1^C$, $b^F = b_0^F b_1^F$, $\delta_t^C = b_0^C \eta_t^C + \varepsilon_t^C$ and $\delta_t^F = b_0^F \eta_t^F + \varepsilon_t^F$. Obviously,

$$\delta_t^C \sim N(0, \sigma^C) \quad \text{with} \quad \sigma^C = \sqrt{(b_0^C \sigma_1^C)^2 + (\sigma_0^C)^2} \quad \text{and} \quad \delta_t^F \sim N(0, \sigma^F) \quad \text{with}$$

$$\sigma^F = \sqrt{(b_0^F \sigma_1^F)^2 + (\sigma_0^F)^2} .$$

Summing up, chartists follow the current price trend,

fundamentalists bet on a fundamental price correction, and both strategies are subject to exogenous noise.

We now come to the central part of the model. In each time step, speculators have to decide which trading rule to follow. This decision depends on the attractiveness of the technical and fundamental trading rule, formalized as

$$A_t^C = c_p^C + c_h W_t^C - c_m^C (P^* - P_t)^2 \quad (8)$$

and

$$A_t^F = c_p^F + c_h W_t^F + c_m^F (P^* - P_t)^2. \quad (9)$$

First of all, speculators may have a behavioral preference for one of the two trading rules. Such a predisposition effect is expressed by parameters c_p^C and c_p^F . Second, speculators may follow the crowd. The attractiveness of a trading rule thus increases with the size of its market share. Parameter $c_h > 0$ captures the strength of speculators' herding behavior. Finally, speculators may assess market circumstances. Although speculators believe in the persistence of bubbles, they know that all bubbles will eventually burst. In particular, speculators perceive a higher probability that a fundamental price correction is about to set in if the price deviates from its fundamental value. How sensitively the attractiveness of the two trading rules reacts to distortions is controlled by parameters $c_m^C > 0$ and $c_m^F > 0$.

To reduce the number of parameters, we compute from (8) and (9) a relative attractiveness function

$$A_t = A_t^F - A_t^C = c_p + c_h (W_t^F - W_t^C) + c_m (P^* - P_t)^2, \quad (10)$$

where $c_p = c_p^F - c_p^C$ and $c_m = c_m^F + c_m^C$. In short, the relative attractiveness of fundamentalism over chartism depends on speculators' predisposition, herding behavior and market assessment.

The market shares of speculators following the representative technical trading rule and the representative fundamental trading rule are determined by

$$W_t^C = \frac{\text{Exp}[dA_{t-1}^C]}{\text{Exp}[dA_{t-1}^C] + \text{Exp}[dA_{t-1}^F]} = \frac{1}{\text{Exp}[d(A_{t-1}^F - A_{t-1}^C)]} = \frac{1}{1 + \text{Exp}[dA_{t-1}]} \quad (11)$$

and

$$W_t^F = \frac{\text{Exp}[dA_{t-1}^F]}{\text{Exp}[dA_{t-1}^C] + \text{Exp}[dA_{t-1}^F]} = \frac{1}{\text{Exp}[-d(A_{t-1}^F - A_{t-1}^C)]} = \frac{1}{1 + \text{Exp}[-dA_{t-1}]} \quad (12)$$

Parameter $d > 0$ is the so-called sensitivity of choice parameter. Since d is a scaling parameter in this model, it can, without loss of generality, be set to $d = 1$. Equations (11) and (12) imply that if the relative attractiveness of fundamentalism over chartism increases, the market share of chartists decreases and the market share of fundamentalists increases. In this sense, speculators exhibit a kind of learning behavior.

To be able to understand the basic functioning of the model, we abstain for the moment from involving interventions by a central authority, i.e. we impose

$$D_t^A = 0. \quad (13)$$

In Sections 2.3 and 2.4, we introduce simple feedback strategies that may or may not stabilize the model dynamics.

Since we assume that the log fundamental value is equal to zero in all simulations, i.e. $P^* = 0$, seven parameters remain to be specified. Franke and Westerhoff (2012) apply the Method of Simulated Moments to estimate these parameters and obtain the following results

$$b^C = 1.500, \sigma^C = 2.147, b^F = 0.120, \sigma^F = 0.708,$$

$$c_p = -0.336, c_h = 1.839, c_m = 19.671.$$

In general terms, the idea behind the Method of Simulated Moments is to match a predefined set of summary statistics, or moments, that capture the main stylized facts of financial markets (for a review of the properties of financial markets see Lux and Ausloos 2002, Sornette 2003,

and Shiller 2005). For this reason, the model parameters are determined via a multi-dimensional grid search such that the moments of a simulated time series come close to the moments of a real financial market time series. What is meant by “close” has to be specified by an objective function. Here it suffices to note that the current model produces – in a quantitatively acceptable manner – excess volatility, fat tails for the distribution of returns, uncorrelated price changes, volatility clustering and long memory effects which, according to Chen *et al.* (2012), belong to the most prominent stylized facts of financial markets.

Figure 1 depicts a representative simulation run. Since the model is calibrated to daily data, the 5000 observations displayed correspond to a time span of about 20 years. The top panel shows the evolution of log prices. In the long run, prices fluctuate around the fundamental value. In the short run, however, prices may deviate substantially from the fundamental value and exhibit severe bubbles and crashes. Despite these long-run price swings, the day-to-day evolution of prices resembles a random walk. The third panel contains the corresponding return time series. Although the fundamental value is constant, price changes are substantial on average and include a number of extreme movements. In addition, periods in which the market is rather calm alternate with periods in which the market is rather volatile. In the fourth panel, the Hill tail index estimator is plotted as a function of the largest returns (in percent). At the 5 percent level, for instance, the Hill tail index is given at 3.65, which corresponds well to observations in real markets. Finally, the bottom two panels depict autocorrelation functions for raw returns and absolute returns, respectively. Whilst returns are essentially uncorrelated and price changes are thus virtually unpredictable, the autocorrelation coefficients of absolute returns are clearly significant and decay slowly over time, witnessing volatility clustering and long memory effects.

++++ Figure 1 about here +++++

In a nutshell, the model functions as follows. As revealed by the second panel, speculators permanently switch between technical and fundamental analysis. Accordingly,

there are periods in which technical traders dominate the market. During these periods, the market is highly volatile and significant bubbles may emerge. However, fundamental analysis becomes increasingly attractive as bubbles grow. If speculators switch from technical analysis to fundamental analysis, then volatility decreases and prices gradually retreat towards their fundamental values. Of course, this development decreases the attractiveness of fundamental trading and may, together with speculators' behavioral preference towards technical analysis, lead directly to a new wave of chartism and instability. Whilst there is permanent ongoing competition between the two trading rules, speculators' herding behavior lends both regimes a degree of persistence, which is responsible for the marked volatility clustering and long memory effect.

2.2 Policy objectives

Since the dynamics of the model is close to the dynamics of actual financial markets, we feel confident that we can use it as an artificial laboratory to run a number of policy experiments. First of all, however, we have to think about how to define the success or failure of an intervention strategy. One advantage of agent-based modeling is that this task is usually quite easy, at least in a technical sense. It seems natural to assume that policy-makers prefer prices to be relatively stable and to be close to a desired target value, e.g. the fundamental value. In addition, we have to check the viability of an intervention strategy. For instance, the central authority should not build up a larger position, nor should the size of an intervention be unreasonably high. In total, we define four statistics to quantify these aspects. These statistics also allow us to compare the consequences of different intervention strategies.

Let T be the underlying sample length for the statistics. We measure the variability of prices by the average absolute log price change. Expressed in percent, this gives us

$$volatility = 100 \frac{1}{T} \sum_{t=1}^T |P_t - P_{t-1}|. \quad (14)$$

To quantify the market's mispricing, one may estimate the average absolute distance between log prices and the log fundamental value. However, the central authority's desired target value for the market price may deviate from the fundamental value. Taking this into account, we define

$$distortion = 100 \frac{1}{T} \sum_{t=1}^T |P^A - P_t|, \quad (15)$$

where P^A is the desired log target value of the central authority. Hence, this measure estimates the average absolute distance between the log price and the central authority's log target value, and is again expressed in percent.

The application of an intervention strategy should not result in the accumulation of a too large position. Therefore, we monitor the growth rate of the central authority's position by calculating

$$growth = \frac{1}{T} \sum_{t=1}^T D_t^A. \quad (16)$$

Ideally, the growth rate is zero. Moreover, we identify the average (absolute) intervention size of a strategy by

$$size = \frac{1}{T} \sum_{t=1}^T |D_t^A|. \quad (17)$$

Naturally, other measures, such as the profitability of an intervention strategy, may be computed. To limit the analysis, we abstain from such extensions.

As we will see, interventions by a central authority will affect the evolution of the trading rules' market shares. Since these market shares are the key to understanding how the model operates, we furthermore report

$$\text{weight } C = \frac{1}{T} \sum_{t=1}^T W_t^C \quad (18)$$

and

$$\text{weight } F = \frac{1}{T} \sum_{t=1}^T W_t^F, \quad (19)$$

i.e. the average market shares of chartists and fundamentalists. Equipped with these statistics, we can now start our policy experiments.

2.3 Targeting long-run fundamentals interventions

Let us start with a simple and, at least at first sight, plausible intervention strategy. Recall that P^A is the central authority's desired log target value. The central authority may seek to drive the price towards the desired target value by submitting buying orders if the price is below the target value and by submitting selling orders if it is above the target value. Based on these considerations, we obtain the intervention strategy

$$D_t^A = e(P^A - P_t), \quad (20)$$

where parameter $e > 0$ denotes the central authority's intervention force. If the central authority's target value is equal to the fundamental value, we call this strategy the (unbiased) targeting long-run fundamentals strategy. Otherwise, we call it the (biased) targeting long-run fundamentals strategy.

Figure 2 illustrates how the (unbiased) targeting long-run fundamentals strategy may affect the model dynamics. Figure 2 is constructed in the same way as Figure 1, except that we set the central authority's intervention force to $e = 0.4$. With respect to market stability, two aspects become immediately apparent. First, prices are now less disconnected from the fundamental value. And indeed, computing the distortion, we find that the average absolute distance between the log price and the log target value decreases from 20.2 percent (Figure 1,

no interventions) to 13.3 percent (Figure 2, current setup). Second, the price variability has increased. The volatility of the time series depicted in Figure 1 is 0.72 percent whilst the volatility of the time series depicted in Figure 2 is 0.86 percent.

How do these changes come about? Of course, by buying when the price is low and selling when the price is high, the central authority manages to reduce the distortion. But this is not the end of the story. There are indirect effects in addition to this direct effect. These indirect effects that become apparent from our computer experiments may amplify or diminish the (first) direct effect of the interventions. Comparing the second panel of Figure 1 with the second panel of Figure 2 reveals that the market share of chartists increases (in numbers from 27 percent to 44 percent). By reducing the distortion, the relative attractiveness of fundamentalism over chartism decreases. Since the market impact of chartists increases, volatility naturally increases. Of course, this offsets part of the central authority's stabilizing interventions. Note that the fat tail property, the unpredictability of prices and the volatility clustering phenomenon remain essentially unaffected by interventions. We clarify why it is also important to scrutinize these statistics in the sequel.

+ + + + + Figure 2 about here + + + + +

Since the results represented in Figure 2 are just an example, we have to generalize our analysis. Figure 3 shows how statistics (14) to (19) depend on the central authority's intervention force. To be precise, parameter e is increased in 50 discrete steps from 0 to 0.5. Moreover, all six statistics are computed, for each of the 50 values of parameter e , as averages over 50 simulation runs with 5000 observations each. The results of this exercise, which reveal another advantage of agent-based policy analysis – namely the generation of vast amounts of data for different policies – may be summarized as follows. Whilst volatility continuously increases as the central authority becomes more aggressive, the distortion decreases at the same time. Note that the effects are quite significant. Volatility increases

from 0.72 percent for $e = 0$ to 1.00 percent for $e = 0.5$ and the distortion, in turn, decreases from 20 percent for $e = 0$ to 11 percent for $e = 0.5$.

Our model allows these changes to be explained. The market shares of chartists and fundamentalists depend on the central authority's intervention force. As parameter e increases from 0 to 0.5, the market share of chartists increases from about 27 percent to around 55 percent, implying that the market share of fundamentalists decreases from approximately 73 percent to about 45 percent. Due to the presence of more destabilizing chartists, the price variability increases. Of course, the reduction in the market share of fundamentalists is disadvantageous for the central authority since the orders placed by fundamentalists help to drive the price towards the fundamental value. At least for the underlying parameter setting, however, the central authority is able to compensate for the loss of these orders. In fact, the central authority brings the price closer towards the fundamental value. Moreover, it seems that interventions are feasible. At least the position of the central authority remains more or less balanced (as the next experiment reveals, this need not always be the case). To sum up, the (unbiased) targeting long-run fundamentals strategy turns out to be a mixed blessing. Prices may be driven closer towards the fundamental value, yet only at the expense of stronger price fluctuations.

++++ Figure 3 about here +++++

Let us now suppose that the central authority tries to push prices above the fundamental value by raising the log target value to $P^A = P^* + 0.25 = 0.25$. Figure 4 gives us an example of what may then happen. The reaction parameter of the central authority is $e = 0.4$. Apparently, the central authority is able to shift the price dynamics upwards, with a few occasional interruptions. It also becomes obvious that the price variability decreases. What is going on here? Since the price is now further away from its fundamental value, technical analysis appears to be less attractive and more speculators opt for fundamental

analysis. As a result, the price variability decreases. However, the impact of fundamentalists is not strong enough to push the price towards the fundamental value. According to the bottom three panels, the fat tail property, the unpredictability of prices and the volatility clustering phenomenon remain more or less unaffected by interventions.

++++ Figure 4 about here +++++

Figure 5 explores the impact of this strategy more systematically by varying the central authority's intervention force between $e = 0$ and $e = 0.5$. The design of Figure 5 is as in Figure 3, except that $P^A = P^* + 0.25 = 0.25$. At first sight, there may be enthusiasm for this strategy. As the intervention force increases, volatility and distortion decrease, which is in line with the central authority's goals. Unfortunately, this strategy will most probably be unviable in the long run. Whilst the magnitude of the average size of interventions is comparable to that in the previous experiment, the central authority ends up with a massive positive position. The reason for this is as follows. On average, fundamentalists now perceive an overvalued market and continuously submit selling orders. In order to prevent a price decrease, the central authority has to offset these orders and, over time, builds up a significant positive position. To sum up, the second strategy also appears to be a mixed blessing. The central authority may decrease the variability of prices and may push prices towards a desired target value for some time, but eventually it has to abort this policy because its position will otherwise become unbounded.

++++ Figure 5 about here +++++

2.4 Leaning against the wind interventions

Let us now study a different, equally simple intervention strategy. In the previous experiments, the central authority attempted to stabilize the dynamics by mimicking the behavior of fundamentalists. In the next experiments, the central authority seeks to stabilize

the dynamics by countering the behavior of chartists. In the following, the central authority thus trades against the current price trend, i.e. it employs the intervention strategy

$$D_t^A = f(P_{t-1} - P_t), \tag{21}$$

where parameter $f > 0$ denotes the central authority’s intervention force. For obvious reasons, this strategy is called the leaning against the wind strategy.

Figure 6 gives us a first impression of how this strategy may affect the model dynamics. The design of Figure 6 is again as in Figure 1 (and as in Figures 2 and 4), except that the central authority’s intervention force is now given by $f = 12$. This strategy’s performance appears to be rather disappointing. Neither does the price seem to be closer to the fundamental value, nor has the variability of prices decreased. Also speculators’ switching behavior seems to be unchanged. Inspecting the other three panels, we realize that there is a change in the autocorrelation function of the returns. In particular, the autocorrelation coefficient of the returns at the first lag is significantly negative, which is unrealistic (we will return to this issue in Section 2.5).

++++ Figure 6 about here +++++

Unfortunately, Figure 7 gives no cause for greater hope. Overall, the leaning against the wind strategy may reduce the distortion somewhat, but at the cost of greater volatility. Why is this the case? For low values of parameter f , the central authority indeed offsets part of the destabilizing (trend-based) orders of chartists, which may reduce the distortion slightly. As a result, the market share of chartists increases to some extent, and with it volatility. Moreover, the central authority may itself increase volatility, as its interventions increase excess demand. A major problem of the leaning against the wind strategy is that it frequently generates trading in the wrong direction. Since financial market returns are essentially uncorrelated, it is obviously hard to counter price trends.

++++ Figure 7 about here +++++

If the central authority increases its intervention force, its orders eventually overcompensate the (trend-based) orders of chartists and start to induce a mean reversion effect, which further dampens the distortion. The chartists' market share and, thus, volatility increase. But all in all, the effects are very moderate and almost negligible. From the last two panels we see that at least the central authority does not build up a larger position. However, the size of its interventions may, for higher values of parameter f , be larger than in the case of the two previous experiments.

2.5 Discussion

We have seen that agent-based models help us to understand how financial markets function and to assess the effects of regulatory policies. However, our approach may appear too mechanical, which may cause an uneasy feeling. It is therefore time to critically review our results. Let us return to the first intervention strategy, i.e. the (unbiased) targeting long-run fundamentals strategy. Recall that parameter c_m captures how strongly the relative attractiveness of fundamentalism over chartism increases as the price deviates from its fundamental value and that this parameter has been estimated for a market environment in which there are no such interventions. Now, speculators who observe that mispricing in a market decreases substantially over time may change their behavior. In particular, they may switch more rapidly to fundamental analysis during the build-up of a bubble, implying, technically, that parameter c_m increases. Should this be the case, then there are on average more fundamentalists in the market and both volatility and distortion are lower. In this sense, the stabilizing effect of this intervention strategy would be underestimated. Of course, speculators adapt to market developments in our model – in the form of their strategy selection. However, this effect, with constant parameters, may be too weak.

There is also a problem with the second intervention strategy – the (biased) targeting long-run fundamentals strategy. Recall that the central authority manages to drive the price towards a desired target value. In the short run, our results may be reasonable. But this is not the case in the long run. Due to the accumulation of a large open position, the strategy is simply not viable. However, speculators may change their behavior. At some point in time, speculators ought to realize that prices will not return towards the fundamental value and, as a result, may base their strategy selection on the central authority’s target value and not on the fundamental value. In addition, speculators who opt for fundamental analysis should then condition their orders on the distance between the target value and the current price. Should such a learning behavior occur, the impact of the biased intervention strategy becomes more or less identical to the impact of the unbiased strategy. A model in which speculators learn long-run equilibrium prices may do a better job here.

The third strategy – the leaning against the wind strategy – is also associated with a problem. It is clear from the penultimate panel of Figure 6 that the central authority introduces a correlation into the price dynamics. To be precise, the autocorrelation coefficient of the returns at the first lag is significantly negative. In reality, we would expect speculators to try to exploit such a pattern. In particular, technical traders should switch from a trend-extrapolation strategy to a contrarian strategy. However, the current model is too simple to be able to take account of this.

Also, we learn that it may be dangerous to perform Monte Carlo studies as in Figure 7. One should at least inspect some of the time series behind the depicted statistics and check whether the model dynamics still makes sense. In case of Figure 7, for instance, the analysis should be stopped for values of parameter f larger than 10 (for values of f smaller than 10 the problem with the autocorrelation function does not occur).

All in all, this gives us clear warnings: agent-based models should not be used too mechanically. But since theoretical reasoning, human subject experiments and empirical

studies have their challenges, too, agent-based models may nevertheless serve as a valuable tool to help policy-makers determine economic policies. Finally, we mention a few other applications to illustrate some of the areas that have already been addressed using agent-based models: Westerhoff (2001) studies the effects of central bank interventions in foreign exchange markets, He and Westerhoff (2005) investigate the impact of price floors and price ceilings on agricultural commodity markets, Pellizzari and Westerhoff (2009) explore the consequences of transaction taxes, Westerhoff (2003) and Yeh and Jang (2010) are concerned with trading halts and price limits, respectively, Hermsen *et al.* (2010) investigate the role of disclosure requirements, Anufriev and Tuinstra (2010) model short-selling constraints, Scalas *et al.* (2005) inspect insider trading and fraudulent behavior, and Brock *et al.* (2009) examine the problems associated with the appearance of an increasing number of hedging instruments in financial markets.

3 Goods market

In this section, we present a simple agent-based goods market model. Note that many agent-based macro models are inspired by agent-based financial market models. For instance, expectations of the market participants play a crucial role in both research fields, and their modeling is often quite similar. Since our agent-based goods market model is able to produce business cycles, we use it to explore whether simple intervention strategies may stabilize fluctuations in economic activity. For this reason, we have to consider again how to quantify the success or failure of the interventions and how to check their viability.

3.1 A simple agent-based goods market model

The model we present in this section stands in the tradition of Samuelson's (1939) famous multiplier-accelerator model. National income adjusts to aggregate demand which, in turn, is composed of consumption, investment and governmental expenditures. For simplicity,

consumption expenditure is proportional to national income. Following Westerhoff (2006a), investment expenditure does not depend on past output changes, as in Samuelson's (1939) model, but on expected future output changes. In the current contribution, firm managers rely on two prediction rules to forecast the future course of the economy. If they rely on extrapolative expectations, they believe that the current trend of national income is persistent. Consequently, they increase their investment expenditure during an upswing and decrease it during a downswing. If they rely on regressive expectations, they believe that national income will return to its long-run equilibrium value. As a result, they increase their investment expenditure if national income falls below this value and decrease it otherwise. Firm managers select their prediction rule at the beginning of every period, namely with respect to predisposition effects, herding behavior and market circumstances. The use of extrapolative and regressive expectations as well as switching behavior between them is well documented in empirical studies (Branch 2004 and Hommes 2011).

Since the model is able to produce business cycles, we use it as an artificial laboratory to study two common intervention strategies. According to one strategy – the trend-offsetting strategy – the government aims at offsetting income trends and thus increases (decreases) its spending when national income has just fallen (risen). According to the other strategy – the level-adjusting strategy – the government seeks to reduce the gap between the actual level of national income and a desired target value. Government expenditure is thus high (low) if national income is below (above) the target value. Note that Baumol (1961) already studies the effects of these two strategies using Samuelson's original model.

Let us now turn to the details of the model (we apply a new notation). National income adjusts to aggregate demand with a one-period production lag. If aggregate demand exceeds (falls short of) production, then production increases (decreases). Therefore, we write

$$Y_{t+1} = Y_t + a(Z_t - Y_t), \quad (22)$$

where Y_t represents national income (at time step t), Z_t denotes aggregate demand and a indicates the goods market's adjustment speed. For simplicity, we set $a = 1$. As a result, national income at time step $t + 1$ equals aggregate demand at time step t , i.e. $Y_{t+1} = Z_t$.

Since our focus is on a closed economy, aggregate demand is defined as

$$Z_t = C_t + I_t + G_t, \quad (23)$$

where C_t , I_t and G_t stand for consumption, (gross) investment and governmental expenditure, respectively.

Consumers' expenditure is proportional to national income

$$C_t = bY_t. \quad (24)$$

The marginal propensity to consume is limited to $0 < b < 1$. Of course, much more interesting specifications including, for instance, income expectations and/or consumer sentiment effects may be assumed in (24).

The interesting part of the model concerns firms' investment behavior. Firms are boundedly rational and select between two representative investment rules. Aggregate investment expenditures are given as

$$I_t = NW_t^C I_t^C + NW_t^F I_t^F, \quad (25)$$

where N is the number of firms, W_t^C is the market share of firms with extrapolative expectations, I_t^C is the investment expenditure of a single firm with extrapolative expectations, W_t^F is the market share of firms with regressive expectations and I_t^F is the investment expenditure of a single firm with regressive expectations (we stick to the labels C and F to represent the two different kinds of behavior). To simplify matters, we normalize the population size of firms to $N = 1$.

Both (representative) investment rules depend on three components: an autonomous component, an expectations-based component and a random component. These are formalized as

$$I_t^C = \bar{I}^C + i_0^C (E_t^C [Y_{t+1}] - Y_t) + \varepsilon_t^C \quad (26)$$

and

$$I_t^F = \bar{I}^F + i_0^F (E_t^F [Y_{t+1}] - Y_t) + \varepsilon_t^F . \quad (27)$$

Autonomous investments are denoted by \bar{I}^C and \bar{I}^F . Parameters $i_0^C > 0$ and $i_0^F > 0$ indicate how strongly investment expenditures react to expected changes in national income, and $\varepsilon_t^C \sim N(0, \sigma_0^C)$ and $\varepsilon_t^F \sim N(0, \sigma_0^F)$ reflect additional random influences.

Firm managers either form extrapolative or regressive expectations. Extrapolative expectations are given by

$$E_t^C [Y_{t+1}] = Y_t + i_1^C (Y_t - Y_{t-1}) + \eta_t^C , \quad (28)$$

where i_1^C is a positive extrapolation parameter. The random variable $\eta_t^C \sim N(0, \sigma_1^C)$ allows for digressions from purely trend-based expectations. Regressive expectations result in

$$E_t^F [Y_{t+1}] = Y_t + i_1^F (Y^* - Y_t) + \eta_t^F . \quad (29)$$

Followers of the regressive rule expect national income to return to its long-run equilibrium level, perceived as Y^* , at adjustment speed $0 < i_1^F < 1$. Random deviations from this principle are summarized by the random variable $\eta_t^F \sim N(0, \sigma_1^F)$.

Combining (26) to (29) and assuming that the random variables in these equations are independent, we obtain the simplified investment functions

$$I_t^C = \bar{I} + i^C (Y_t - Y_{t-1}) + \delta_t^C \quad (30)$$

and

$$I_t^F = \bar{I} + i^F (Y^* - Y_{t-1}) + \delta_t^F, \quad (31)$$

where $\bar{I} = \bar{I}^C = \bar{I}^F$, $i^C = i_0^C i_1^C$, $i^F = i_0^F i_1^F$, $\delta_t^C = i_0^C \eta_t^C + \varepsilon_t^C$ and $\delta_t^F = i_0^F \eta_t^F + \varepsilon_t^F$. Note

that $\delta_t^C \sim N(0, \sigma^C)$ with $\sigma^C = \sqrt{(i_0^C \sigma_1^C)^2 + (\sigma_0^C)^2}$ and that $\delta_t^F \sim N(0, \sigma^F)$ with

$$\sigma^F = \sqrt{(i_0^F \sigma_1^F)^2 + (\sigma_0^F)^2}.$$

How do firms select their investment rules? Analogous to the financial market model, we assume that firms compare the attractiveness of the rules and that the mass of them select the most attractive investment rule. Let us first discuss the attractiveness of the rules, which are defined as

$$A_t^C = c_p^C + c_h W_t^C - c_m^C (Y^* - Y_t)^2 \quad (32)$$

and

$$A_t^F = c_p^F + c_h W_t^F + c_m^F (Y^* - Y_t)^2. \quad (33)$$

Accordingly, firms may have different behavioral preferences for the rules, indicated by parameters c_p^C and c_p^F . In addition, firms may be sensitive to herding dynamics, where parameter $c_h > 0$ controls the strength of this effect. Finally, firms assess current market circumstances. The more extreme the business cycle becomes, the more attractive the regressive forecasting rule appears to them. Parameters $c_m^C > 0$ and $c_m^F > 0$ calibrate how quickly firms switch from extrapolative to regressive expectations as the business cycle develops.

We employ a relative attractiveness function to reduce the number of parameters.

Taking the difference between (33) and (32) yields

$$A_t = A_t^F - A_t^C = c_p + c_h (W_t^F - W_t^C) - c_m (Y^* - Y_t)^2, \quad (34)$$

where $c_p = c_p^F - c_p^C$ and $c_m = c_m^F + c_m^C$. To sum up, the relative attractiveness of regressive

expectations over extrapolative expectations depends on firms' predisposition, herding behavior and market assessment.

The market shares of firms forming extrapolative and regressive expectations is formalized by

$$W_t^C = \frac{\text{Exp}[dA_{t-1}^C]}{\text{Exp}[dA_{t-1}^C] + \text{Exp}[dA_{t-1}^F]} = \frac{1}{\text{Exp}[d(A_{t-1}^F - A_{t-1}^C)]} = \frac{1}{1 + \text{Exp}[dA_{t-1}]} \quad (35)$$

and

$$W_t^F = \frac{\text{Exp}[dA_{t-1}^F]}{\text{Exp}[dA_{t-1}^C] + \text{Exp}[dA_{t-1}^F]} = \frac{1}{\text{Exp}[-d(A_{t-1}^F - A_{t-1}^C)]} = \frac{1}{1 + \text{Exp}[-dA_{t-1}]} \quad (36)$$

Parameter $d > 0$ describes how sensitively firms react to changes in the investment rules' relative attractiveness. Again we set, without loss of generality, $d = 1$.

For the moment, governmental expenditure is constant, i.e.

$$G_t = \bar{G}, \quad (37)$$

where $\bar{G} > 0$. In Sections 3.3 and 3.4, we discuss the impact of countercyclical intervention strategies on the model dynamics and their long-run viability.

Firm managers believe that the long-run equilibrium value of national income is given by the Keynesian multiplier solution, i.e. $Y^* = (\bar{I} + \bar{G})/(1-b)$. In total, therefore, ten parameters remain to be specified. We choose:

$$b = 0.9, \bar{I} = 0.3, i^C = 1.4, \sigma^C = 0.015, i^F = 0.8, \sigma^F = 0.015, \bar{G} = 0.2, \\ c_p = -0.45, c_h = 1.2, c_m = 500.$$

This time, we selected the model parameters by hand such that the dynamics of the model resembles actual business cycles, at least to some degree. Obviously, a calibration approach is more informal than an estimation approach, such as the use of the Method of Simulated Moments in the previous example. One should therefore be careful when interpreting the

results. Whilst quantitative statements are virtually impossible to justify, qualitative reasoning may nevertheless be possible.

Figure 8 contains an example of the model dynamics. The depicted time series last 100 periods which should be interpreted as a time span of 100 years. The top panel shows that national income oscillates around $Y^* = 5$ (horizontal gray line) and that business cycles last, on average, around eight years. The second, third and fifth panels depict the paths of consumption, investment and governmental expenditure, respectively. Note that the first three time series evolve procyclically, as is the case in reality. In addition, the magnitude of consumption changes and investment changes are roughly comparable. Since total investment expenditure is lower than total consumption expenditure, the relative variability of investment expenditure is larger than the relative variability of consumption expenditure (empirical properties of actual business cycles are summarized in Stock and Watson 1999). Although the power of the model should not be overstated, given its simplicity it does the job adequately.

++++ Figure 8 about here +++++

The penultimate panel of Figure 8 presents the market shares of extrapolating firms and helps us to comprehend how the model functions. If the majority of firms opt for extrapolative expectations, the economy is unstable and national income drifts away from its long-run equilibrium value. As a result, the attractiveness of regressive expectations increases. Since more and more firms turn to regressive expectations, the economy becomes stabilized and national income returns towards its long-run equilibrium value. Due to the prevailing conditions and firms' behavioral preference for extrapolative expectations, the economy, however, receives its next destabilizing impulse. This pattern repeats itself in a more or less complex manner. For instance, herding effects may easily prolong stable and unstable periods, thereby affecting the amplitude and frequency of business cycles.

Despite the random shocks, there is still some regularity in the business cycles, in particular in the first 50 periods. We briefly add here that, in the absence of exogenous shocks, our deterministic goods market model produces quasi-periodic dynamics whilst our deterministic financial market model is characterized by fixed point dynamics. However, both models are highly nonlinear and exogenous shocks trigger irregular transients.

3.2 Policy objectives

We introduce four statistics to evaluate the success of the intervention strategies. It seems reasonable to assume that policy-makers prefer national income to be relatively stable and close to a desired target value. In addition, the interventions should on average be balanced and the size of the interventions should be not too large. The sample length for which we compute these statistics is again given by T .

The variability of national income is measured by its average absolute relative change. Expressed in percent, we have

$$volatility = 100 \frac{1}{T} \sum_{t=1}^T |Y_t - Y_{t-1}| / Y_{t-1}. \quad (38)$$

Let Y^A be the policy-makers' desired target value for national income. In this sense, a natural measure for an "undesired" output gap, also expressed in percent, is

$$distortion = 100 \frac{1}{T} \sum_{t=1}^T |Y^A - Y_t| / Y^A. \quad (39)$$

Since the policy-makers aim at a balanced net position, we report the growth rate of their position by calculating

$$growth = \frac{1}{T} \sum_{t=1}^T (G_t - \bar{G}). \quad (40)$$

In addition, the average (absolute) size of an intervention strategy is given by

$$size = \frac{1}{T} \sum_{t=1}^T |G_t - \bar{G}|. \quad (41)$$

Note that by subtracting \bar{G} in (40) and (41), these two measures take only the active part of the intervention strategies into account. Although, of course, other measures may be computed, we abstain from such extensions.

We also keep track of the average market shares of the two investment rules by defining

$$weight\ C = \frac{1}{T} \sum_{t=1}^T W_t^C \quad (42)$$

and

$$weight\ F = \frac{1}{T} \sum_{t=1}^T W_t^F. \quad (43)$$

These statistics are again the key to understanding how the model functions.

3.3 Level-adjusting interventions

The first rule we explore is the so-called level-adjusting rule. According to this rule, the government increases (decreases) its expenditure if national income is below (above) its desired target value in the hope that national income will thereby be pushed upwards (downwards). Formally, we have

$$G_t = \bar{G} + e(Y^A - Y_t), \quad (44)$$

where parameter $e > 0$ indicates the government's aggressiveness. In analogy to the financial market examples, let us refer to an (unbiased) level-adjusting rule if the government's target value is equal to Y^* , i.e. to the long-run equilibrium value of national income as perceived by firms, and to a (biased) level-adjusting rule otherwise.

Figure 9 illustrates how an (unbiased) level-adjusting rule may affect the model dynamics. The design of Figure 9 is as in Figure 8, except that $e = 0.5$ and $Y^A = 5$. A comparison of Figures 8 and 9 reveals that the interventions reduce the amplitude of business cycles but simultaneously increase their frequency. Whilst this placates consumption expenditures, investment expenditure appears to be more volatile. What is going on here? By increasing expenditure when national income is low and decreasing it when national income is high, the government indeed manages to drive national income closer to $Y^A = Y^* = 5$. On average, however, extrapolative expectations now appear more attractive to firms. Since the central authority also reverses the course of national income more frequently via its interventions, the length of business cycles is shortened.

++++ Figure 9 about here +++++

Figure 10 captures the effects of (unbiased) level-adjusting interventions in more detail by showing how our policy measures respond to stronger intervention forces. In Figure 10, parameter e is increased in 50 discrete steps from 0 to 1 and all statistics are computed as averages over 50 simulation runs with 5000 observations each. The main results are as follows. First of all, volatility increases, i.e. national income changes more strongly if the government reacts more aggressively. The good news is that the distortion decreases, i.e. the government manages to drive national income closer towards its target value. For $e = 0$, for instance, the distortion is about 0.43 percent whilst for $e = 1$ it is only about 0.33 percent, a reduction of about one fourth.

Note that firms switch from regressive expectations to extrapolative expectations as parameter e increases. This change is most likely to dampen the stabilizing effect of (unbiased) level-adjusting interventions, contributing to greater volatility. As indicated by the bottom two panels of Figure 10, the government's average net position is close to zero, yet the size of its interventions increases with intervention force. To put the numbers into perspective,

for $e = 0.6$, for instance, the average size of the interventions is about 0.01, which corresponds to a stimulus of 0.2 percent of national income per year, a number which should be accomplishable.

++++ Figure 10 about here +++++

Figure 11 presents a simulation run for the (biased) level-adjusting rule. The design of Figure 11 is as in Figure 8, except that $e = 0.5$ and $Y^A = 5.05$ (i.e. the target value of the government is one percent above $Y^* = 5$). Obviously, the government manages to increase the average level of national income. In addition, whilst the amplitude of business cycles has decreased, the frequency of business cycles is higher than before (see Figure 8). Also the relevance of extrapolative expectations has diminished.

++++ Figure 11 about here +++++

Let us inspect Figure 12 to understand what is happening here. By supporting the target value $Y^A = 5.05$, the average level of national income increases and thus the distortion decreases. Moreover, more firms now rely on regressive expectations. Since this creates a downward pressure for national income (investment expenditures based on regressive expectations are lower), the government has to stimulate the economy in most time steps. Indeed, as revealed by the bottom left panel of Figure 12, the government's average net position is no longer neutral and, over time, this strategy is virtually unviable (although the average absolute size of the interventions is roughly comparable to the previous strategy). For completeness, note that there is also a slight increase in volatility.

++++ Figure 12 about here +++++

3.4 Trend-offsetting interventions

The last strategy we investigate is a so-called trend-offsetting strategy, given by

$$G_t = \bar{G} + f(Y_{t-1} - Y_t). \tag{44}$$

Since f is a positive parameter, the government increases its expenditure if national income decreases, and vice versa.

Figure 13 depicts how this strategy may affect the dynamics. The difference between Figure 8 and Figure 13 is that $f = 0$ in Figure 8 whilst $f = 0.5$ in Figure 13. Interestingly, we may finally have a strategy that is capable of stabilizing the dynamics. As suggested by the first panel of Figure 13, both the amplitude and the frequency of business cycles decrease due to the interventions. Although more firms now rely on extrapolative expectations, changes in national income have not increased. Of course, a government that manages to weaken the trend of national income automatically tames the destabilizing impact of extrapolative expectations.

++++ Figure 13 about here +++++

Figure 14 confirms these promising results. If the government increases its intervention force, then volatility and distortion decrease. Whilst the market share of firms forming regressive expectations decreases, the dynamics nevertheless becomes stabilized. As already mentioned, the destabilizing impact of extrapolative expectations decreases if trends in the business cycle decrease. But why does this strategy work in the business cycle model but not in the financial market model? Recall that price changes are unpredictable in the financial market model and a central authority that trades in the direction of the most recent price trend trades with a probability of 50 percent in the direction of the current price trend. In case of business cycles, the government makes errors less frequently. The intervention by the government only goes with the trend at the turning point of a business cycle. Otherwise it effectively counters the trend.

++++ Figure 14 about here +++++

3.5 Discussion

Let us critically review the results of the last two sections and start with the (unbiased) level-adjusting strategy. By changing the features of business cycles, firms may be expected to adjust their behavior. In our model, firms adjust their behavior via the selection process of the prediction rules. If the attractiveness of regressive expectations decreases, for instance, firms will opt for extrapolative expectations more frequently. However, the way in which firms perceive the attractiveness of the prediction rules remains constant (the parameters are fixed). One may expect in reality that if the amplitude of business cycles decreases, firms will take this into account and will consequently switch earlier towards regressive expectations during the build-up of a boom or recession. This would presumably further stabilize the dynamics, i.e. we may currently underestimate the effectiveness of this strategy.

What about the (biased) level-adjusting strategy? If firms realize that national income fluctuates above their perceived long-run equilibrium value, they should take this observation into account when selecting their prediction rules and forming their expectations. In our simple model, this is not the case. If firms did this, the results of the (biased) strategy would ultimately converge towards the results of the (unbiased) strategy. On the other hand, learning in a macroeconomic context may take a considerable length of time. For instance, the duration of three business cycles, after which a permanent change in the level of national income may become apparent, may last 25 years. From this perspective, this aspect should presumably not be regarded as too critical. The illustrated results may be reasonable for a few years, at least, albeit at the cost that the government's position becomes non-neutral.

The trend-offsetting strategy faces a similar problem as the (unbiased) level-adjusting strategy. In the end, firms will realize that the amplitude of business cycles has declined and will thus adapt their behavior. If they switch more rapidly to regressive expectations, the dynamics may even be more stabilized. On the other hand, note that the effectiveness of this strategy depends on the regularity of business cycles. The more irregular business cycles are, the less effective the trend-offsetting strategy will be. Since actual business cycles may be

more irregular than the business cycles in Figure 8, we may be overstating the functioning of the trend-offsetting strategy.

Small-scale agent-based macro models are currently emerging; there are not yet many policy applications. Nevertheless, further examples include Westerhoff (2006b), Brazier *et al.* (2008), Westerhoff and Hohnisch (2010), de Grauwe (2010), Lines and Westerhoff (2010, 2012) and Anufriev *et al.* (2012). Finally, some authors have started to connect agent-based models from the real sector with agent-based financial market models. This research area seems to be promising, also with a view to policy applications. Examples include Lengnick and Wohltmann (2012) and Westerhoff (2012).

4 Summary and outlook

Agent-based modeling may serve as a valuable tool for economic policy analysis in addition to theoretical reasoning, human subject experiments and empirical studies. In this contribution, we review the extent to which agent-based models are currently suitable for evaluating the effectiveness of certain regulatory policies. As our analysis shows, agent-based modeling is associated with a number of natural advantages, some of which are mentioned here:

- Agent-based models give us fresh insights into how economic systems function and, thereby, how regulatory policies may shape their dynamics. For instance, regulatory policies frequently have an obvious direct effect, but their indirect effects are often much less clear. By disentangling direct effects and indirect effects, agent-based models help us to grasp the impact of regulatory policies in more detail. Agent-based models also reveal the limits of regulatory policies. We can learn what to expect and what not to expect from regulatory policies.
- Agent-based models can also be used to pre-test the effectiveness of newly proposed policies. Moreover, we can even use agent-based models to improve these policies or to

design alternative policies. For instance, an agent-based model may reveal that a nonlinear intervention rule does a better job of stabilizing markets than its linear counterpart.

- Agent-based models enable us to control for all exogenous shocks and to simulate extreme events. If we are interested in how a certain policy works during a particular type of crisis, say a dramatic downward shift of the equilibrium value of national income, we may simply add such a crisis to our analysis.
- Agent-based models allow us to generate as much data as necessary. Compared to empirical studies and human subject experiments where data is typically limited (or simply not available), modern computers enable vast amounts of observations to be computed. This is quite important: due to the appearance of infrequent market frenzies, many statistics such as volatility measures converge relatively slowly and wrong conclusions may be drawn if the data is collected in a rather calm or turbulent period.
- Agent-based models enable all variables to be measured precisely. In reality, it is often difficult to identify the exact equilibrium value of a financial market or of the real economy. In agent-based models, this task is usually quite simple. Other variables, such as expectations and/or transactions of market participants, may also be recorded.
- In agent-based models, the intensity of a policy can be varied smoothly. In contrast, many empirical studies are based on periods in which a policy with a constant strength was applied. By gradually increasing the intensity of a policy, agent-based models may reveal nontrivial effects that are precluded at coarser scales. Other types of sensitivity analysis, such as the use of different model parameters or functional specifications of the model's building blocks, are also possible.

Of course, the starting point of the analysis should always be an appropriate agent-based model. The appropriateness of the underlying model decides whether results are obtained that are interesting from a quantitative perspective, as in our financial market

example, or which have a more qualitative outlook, as in our goods market example. In this respect, three aspects deserve attention:

- First, the model ideally possesses an empirical microfoundation, meaning that its main building blocks should be supported by empirical evidence. For instance, speculators' use of technical and fundamental analysis, as assumed in our agent-based financial market model, is well documented in the empirical literature. At first sight, the setup of agent-based models may seem ad hoc to outsiders. In our view, however, this is not the case, at least not as long as the models' main building blocks are in line with reality.
- Second, the internal functioning of the underlying model should be convincing. For instance, complex dynamics emerge in our agent-based financial market model since speculators switch between destabilizing technical trading rules and stabilizing fundamental trading rules. Bubbles are thus initiated by a wave of chartism and crashes are triggered by a surge of fundamentalism. Clearly, it would not sound very plausible if this were the other way around.
- Third, the data generated by the model should be as realistic as possible. In particular, an agent-based model should be able to mimic the main stylized facts of a market for which it is developed. Here it is encouraging to see that more and more agent-based models are being estimated rather than merely calibrated (by hand), which lends these models a considerable amount of additional support.

If these requirements are fulfilled, agent-based models may be well suitable for conducting policy experiments. The following steps have to be considered:

- One important task is to define a set of measures that allow a policy's success or failure to be evaluated. However, it is equally important to determine whether a policy is viable in the long run. A policy that is able to stabilize the markets but causes unsustainable costs is obviously of not much use.

- Moreover, a policy has to be properly implemented in the agent-based model. In our two examples, the intervention policies alter the markets' excess demands. Other policies may affect the attractiveness of the market participants' strategies or other model components. Fortunately, agent-based models are relatively flexible in this respect, yet this modeling aspect is crucial and should not be underestimated.
- Finally, we have seen that it may be dangerous to apply agent-based models too mechanically. It is thus vital to check whether the agents' behavior still makes sense after the imposition of a new policy and whether the resulting dynamics is still reasonable.

To conclude, our economy is a complex adaptive system and nonlinearities often make it very difficult to anticipate the consequences of regulatory policies. The use of agent-based models offers us insights into the functioning of economic systems that are otherwise precluded. We are convinced that agent-based models are an excellent tool for enhancing our understanding of regulatory policies, in particular, if they are empirically supported, and look forward to more exciting research in this area.

References

- Anufriev, Mikhail and Jan Tuinstra. The Impact of Short-Selling Constraints on Financial Market Stability in a Model with Heterogeneous Agents. CeNDEF Working Paper 10-03, Amsterdam: University of Amsterdam, 2010.
- Anufriev, Mikhail, Assenza, Tiziana, Hommes, Cars and Domenico Massaro. Interest Rate Rules and Macroeconomic Stability under Heterogeneous Expectations. *Macroeconomic Dynamics* (2012): in press.
- Baumol, William. Pitfalls in Contracyclical Policies: Some Tools and Results. *Review of Economics and Statistics* 43 (1961): 21-26.
- Branch, William. The Theory of Rational Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations. *Economic Journal* 114 (2004): 592-621.
- Branch, William and Bruce McGough. A New-Keynesian Model with Heterogeneous Expectations. *Journal of Economic Dynamics and Control* 33 (2009): 1036-1051.
- Brazier, Alex, Harrison, Richard, King, Mervyn and Tony Yates. The Danger of Inflating Expectations of Macroeconomic Stability: Heuristic Switching in an Overlapping Generations Monetary Model. *International Journal of Central Banking* 4 (2008): 219-254.
- Brock, William and Cars Hommes. Heterogeneous Beliefs and Routes to Chaos in a Simple Asset Pricing Model. *Journal of Economic Dynamics Control* 22 (1998): 1235-1274.
- Brock, William, Hommes, Cars and Florian Wagener. More Hedging Instruments may Destabilize Markets. *Journal of Economic Dynamics and Control* 33 (2009): 1912-1928.
- Chen, Shu-Heng, Chang, Chia-Ling and Ye-Rong Du. Agent-Based Economic Models and Econometrics. *Knowledge Engineering Review* 27 (2012): 187-219.
- Chiarella, Carl. The Dynamics of Speculative Behavior. *Annals of Operations Research* 37 (1992): 101-123.
- Chiarella, Carl, Dieci, Roberto and Xue-Zhong He. "Heterogeneity, Market Mechanisms, and Asset Price Dynamics". In *Handbook of Financial Markets: Dynamics and Evolution*, edited by Thorsten Hens and Klaus Reiner Schenk-Hoppé, 277-344. Amsterdam: North-Holland, 2009.
- Day, Richard and Weihong Huang. Bulls, Bears and Market Sheep. *Journal of Economic Behavior and Organization* 14 (1990): 299-329.
- De Grauwe, Paul, Dewachter, Hans and Mark Embrechts. *Exchange Rate Theory – Chaotic Models of Foreign Exchange Markets*. Oxford: Blackwell, 1993.
- De Grauwe, Paul. Animal Spirits and Monetary Policy. *Economic Theory* 47 (2010): 423-457.

- Farmer, Doyne and Shareen Joshi. The Price Dynamics of Common Trading Strategies. *Journal of Economic Behavior and Organization* 49 (2002): 149-171.
- Franke, Reiner. "Microfounded Animal Spirits and Goodwinian Income Distribution Dynamics". In *Effective Demand, Income Distribution and Growth. Research in Memory of the Work of Richard M. Goodwin*, edited by Peter Flaschel and Michael Landesmann, 372-398. London: Routledge, 2008.
- Franke, Reiner. Microfounded Animal Spirits in the New Macroeconomic Consensus. *Studies in Nonlinear Dynamics and Econometrics* 16 (2012): Issue 4, Article 4.
- Franke, Reiner and Frank Westerhoff. Structural Stochastic Volatility in Asset Pricing Dynamics: Estimation and Model Contest. *Journal of Economic Dynamics and Control* 26, (2012): 1193-1211.
- Graham, Benjamin and David Dodd. *Security Analysis*. New York: McGraw-Hill, 1951.
- He, Xue-Zhong and Frank Westerhoff. Commodity Markets, Price Limiters and Speculative Price Dynamics. *Journal of Economic Dynamics and Control* 29 (2005): 1577-1596.
- He, Xue-Zhong and Youwei Li. Power-Law Behaviour, Heterogeneity, and Trend Chasing. *Journal of Economic Dynamics and Control* 31 (2007): 3396-3426.
- Hens, Thorsten and Klaus Reiner Schenk-Hoppé. *Handbook of Financial Markets: Dynamics and Evolution*. Amsterdam: North-Holland, 2009.
- Hermesen, Oliver, Witte, Björn-Christopher and Frank Westerhoff. Disclosure Requirements, the Release of New Information and Market Efficiency: New Insights from Agent-Based Models. *Economics: The Open-Access, Open-Assessment E-Journal* 4 (2010): Article ID 2010-7.
- Hommes, Cars and Florian Wagener. "Complex Evolutionary Systems in Behavioral Finance". In *Handbook of Financial Markets: Dynamics and Evolution*, edited by Thorsten Hens and Klaus Reiner Schenk-Hoppé, 217-276. Amsterdam: North-Holland, 2009.
- Hommes, Cars. The Heterogeneous Expectations Hypothesis: Some Evidence from the Lab. *Journal of Economic Dynamics and Control* 35 (2011): 1-24.
- Kirman, Alan. "Epidemics of Opinion and Speculative Bubbles in Financial Markets". In *Money and Financial Markets*, edited by Mark Taylor, 354-368. Oxford: Blackwell, 1991.
- LeBaron, Blake, Arthur, Brian and Richard Palmer. Time Series Properties of an Artificial Stock Market. *Journal of Economic Dynamics and Control* 23 (1999): 1487-1516.
- Lengnick, Matthias and Hans-Werner Wohltmann. Agent-Based Financial Markets and New Keynesian Macroeconomics: A Synthesis. *Journal of Economic Interaction and Coordination* (2012): in press.

- Lines, Marji and Frank Westerhoff. Inflation Expectations and Macroeconomic Dynamics: The Case of Rational versus Extrapolative Expectations. *Journal of Economic Dynamics and Control* 34 (2010): 246-257.
- Lux, Thomas. Herd Behaviour, Bubbles and Crashes. *Economic Journal* 105 (1995): 881-896.
- Lux, Thomas and Marcel Ausloos. "Market Fluctuations I: Scaling, Multiscaling, and their Possible Origins". In *Science of Disaster: Climate Disruptions, Heart Attacks, and Market Crashes*, edited by Armin Bunde, Jürgen Kropp and Hans Joachim Schellnhuber, 373-410. Berlin: Springer 2002.
- Lux, Thomas. "Stochastic Behavioural Asset-Pricing Models and the Stylized Facts". In *Handbook of Financial Markets: Dynamics and Evolution*, edited by Thorsten Hens and Klaus Reiner Schenk-Hoppé, 161-216. Amsterdam: North-Holland, 2009.
- Menkhoff, Lukas and Mark Taylor. The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis. *Journal of Economic Literature* 45 (2007): 936-972.
- Murphy, John. *Technical Analysis of Financial Markets*. New York: New York Institute of Finance, 1999.
- Neely, Christopher. An Analysis of Recent Studies of the Effect of Foreign Exchange Intervention. *Federal Reserve Bank of St. Louis Review* 87 (2005): 685-717.
- Pellizzari, Paulo and Frank Westerhoff. Some Effects of Transaction Taxes under Different Microstructures. *Journal of Economic Behavior and Organization* 72 (2009): 850-863.
- Rosser, Barkley. *Handbook of Research on Complexity*. Cheltenham: Edward Elgar, 2009.
- Samuelson, Paul. Interactions between the Multiplier Analysis and the Principle of Acceleration. *Review of Economic Statistics* 21 (1939): 75-78.
- Scalas, Enrico, Cincotti, Silvano, Dose, Christian and Marco Raberto. "Fraudulent Agents in an Artificial Financial Market". In *Nonlinear Dynamics and Heterogeneous Interacting Agents*, edited by Thomas Lux, Stefan Reitz and Eleni Samanidou, 317-326. Berlin: Springer, 2005.
- Shiller, Robert. *Irrational Exuberance*. Princeton: Princeton University Press, 2005.
- Sornette, Didier. *Why Stock Markets Crash*. Princeton: Princeton University Press, 2003.
- Stock, James and Mark Watson. "Business Cycle Fluctuations in U.S. Macroeconomic Time Series". In *Handbook of Macroeconomics*, edited by John Taylor and Michael Woodford, 3-64. Amsterdam, North-Holland, 1999.
- Tesfatsion, Leigh and Kenneth Judd. *Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics*. Amsterdam: North-Holland, 2006.

- Tuinstra, Jan and Florian Wagener. On Learning Equilibria. *Economic Theory* 30 (2007): 493-513.
- Westerhoff, Frank. Speculative Behavior, Exchange Rate Volatility, and Central Bank Intervention. *Central European Journal of Operations Research* 9 (2001): 31-50.
- Westerhoff, Frank. Speculative Markets and the Effectiveness of Price Limits. *Journal of Economic Dynamics and Control* 28 (2003): 493-508.
- Westerhoff, Frank. Samuelson's Multiplier-Accelerator Model Revisited. *Applied Economics Letters* 13 (2006a): 89-92.
- Westerhoff, Frank. Business Cycles, Heuristic Expectation Formation and Contracyclical Policies. *Journal of Public Economic Theory* 8 (2006b): 821-838.
- Westerhoff, Frank and Roberto Dieci. The Effectiveness of Keynes-Tobin Transaction Taxes when Heterogeneous Agents can Trade in Different Markets: A Behavioral Finance Approach. *Journal of Economic Dynamics and Control* 30 (2006): 293-322.
- Westerhoff, Frank. The Use of Agent-Based Financial Market Models to Test the Effectiveness of Regulatory Policies. *Jahrbücher für Nationalökonomie und Statistik* 228 (2008): 195-227.
- Westerhoff, Frank. "Exchange Rate Dynamics: A Nonlinear Survey". In *Handbook of Research on Complexity*, edited by Barkley Rosser, 287-32. Cheltenham: Edward Elgar, 2009.
- Westerhoff, Frank and Martin Hohnisch. Consumer Sentiment and Countercyclical Fiscal Policies. *International Review of Applied Economics* 24 (2010): 609-618.
- Westerhoff, Frank. Interactions between the Real Economy and the Stock Market. *Discrete Dynamics in Nature and Society* 2012 (2012): Article ID 504840.
- Yeh, Chia-Hsuan and Chun-Yi Yang. Examining the Effectiveness of Price Limits in an Artificial Stock Market. *Journal of Economic Dynamics and Control* 34 (2010): 2089-2108.

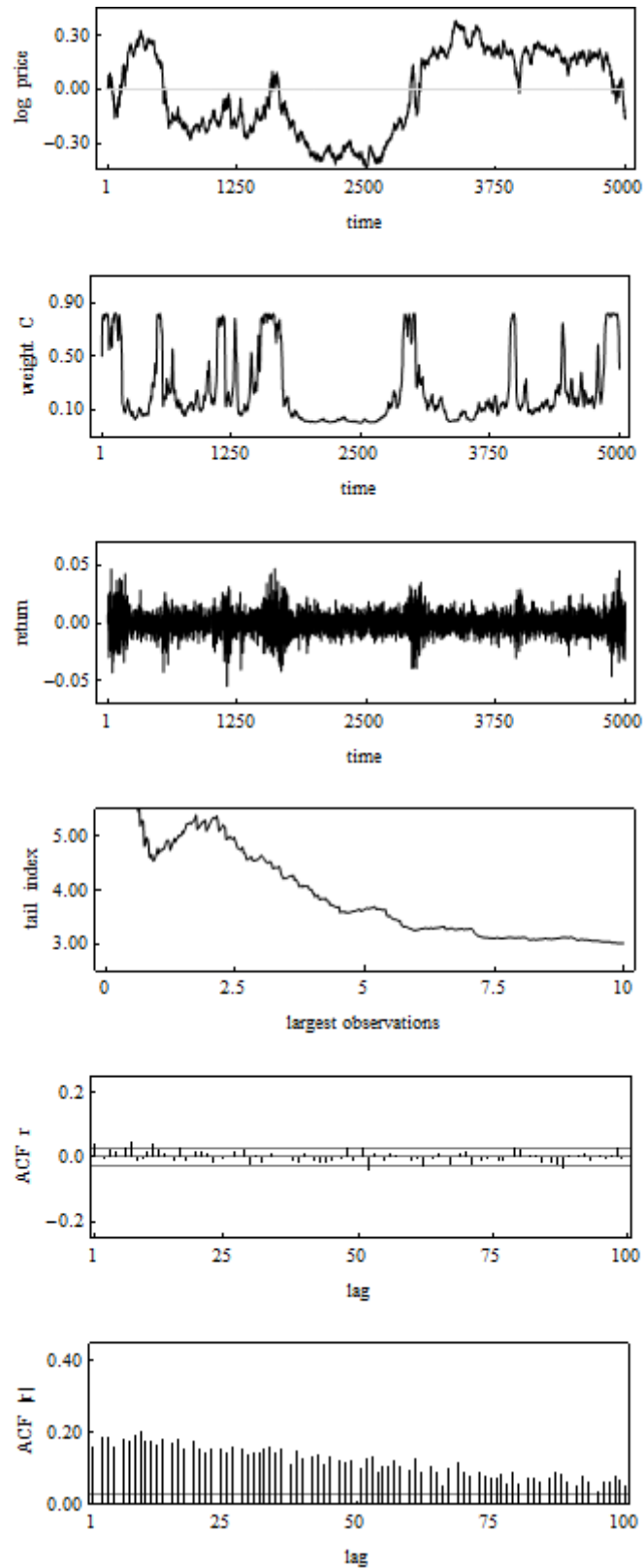


Figure 1: The dynamics of the agent-based financial market model without regulations. Parameter setting as in Section 2.

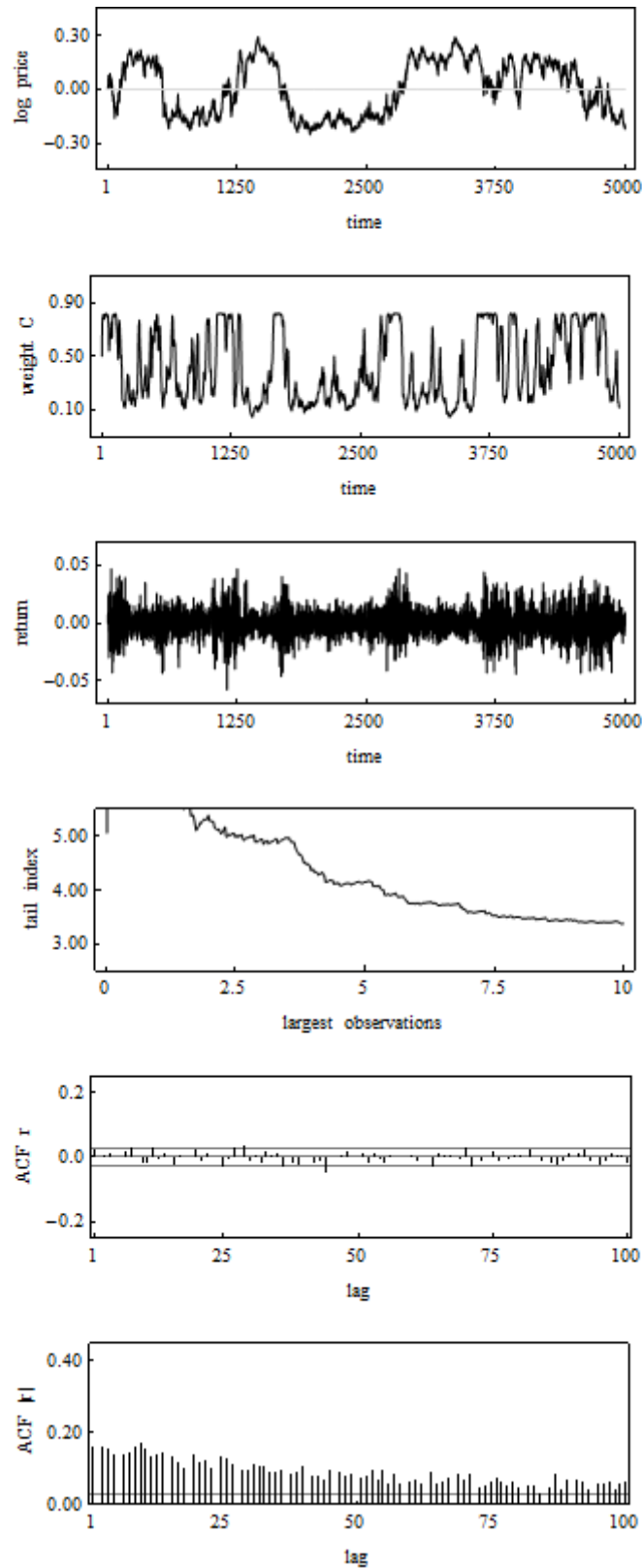


Figure 2: The dynamics of the agent-based financial market model with (unbiased) targeting long-run fundamentals interventions. Parameter setting as in Figure 1. In addition, parameter $e = 0.4$ and log target price $P^A = 0$.

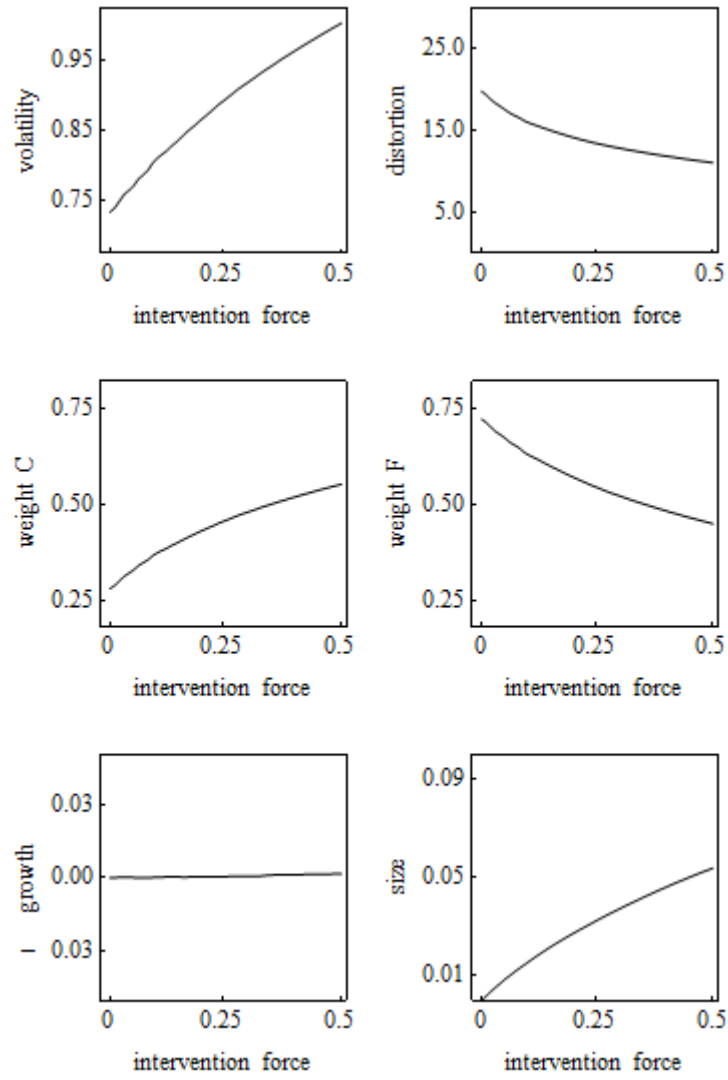


Figure 3: Some effects of (unbiased) targeting long-run fundamentals interventions. Parameter setting as in Figure 1. In addition, parameter e is increased from 0 to 0.5 and the log target price is $P^A = 0$.

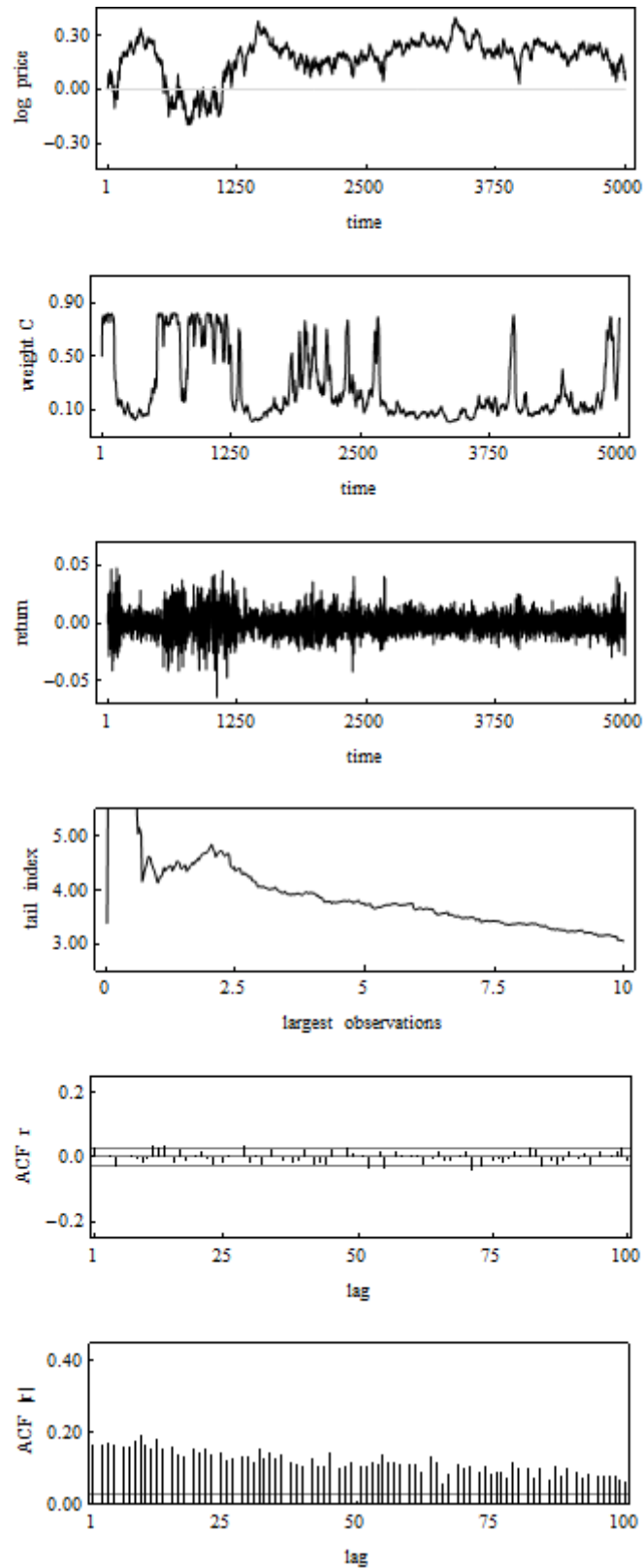


Figure 4: The dynamics of the agent-based financial market model with (biased) targeting long-run fundamentals interventions. Parameter setting as in Figure 1. In addition, parameter $e = 0.4$ and log target price $P^A = 0.25$.

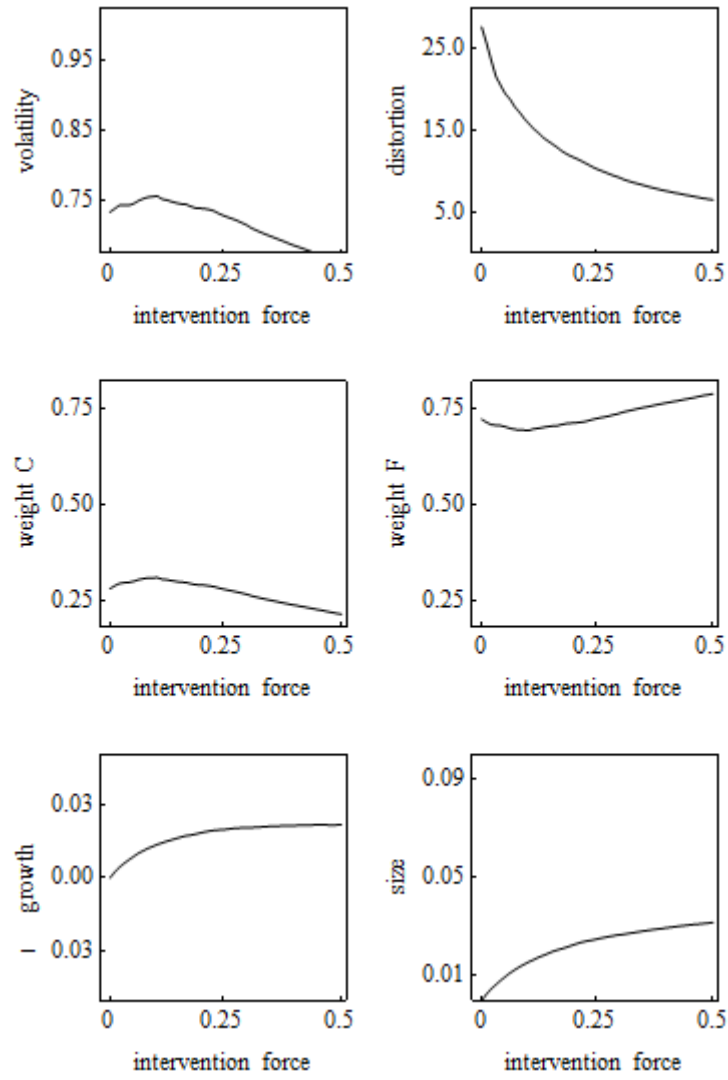


Figure 5: Some effects of biased targeting long-run fundamentals interventions. Parameter setting as in Figure 1. In addition, parameter e is increased from 0 to 0.5 and the log target price is $P^A = 0.25$.

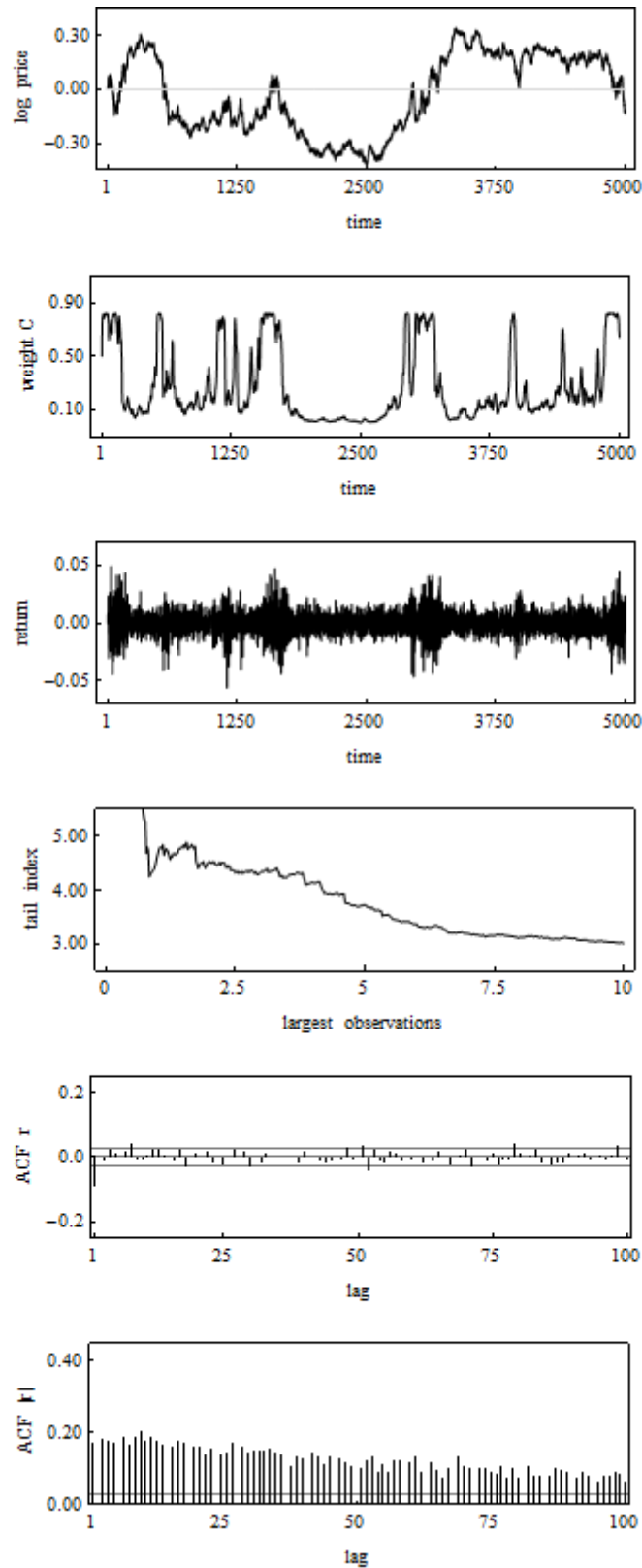


Figure 6: The dynamics of the financial market model with leaning against the wind interventions. Parameter setting as in Figure 1. In addition, parameter $f = 12$ and log target price $P^A = 0$.

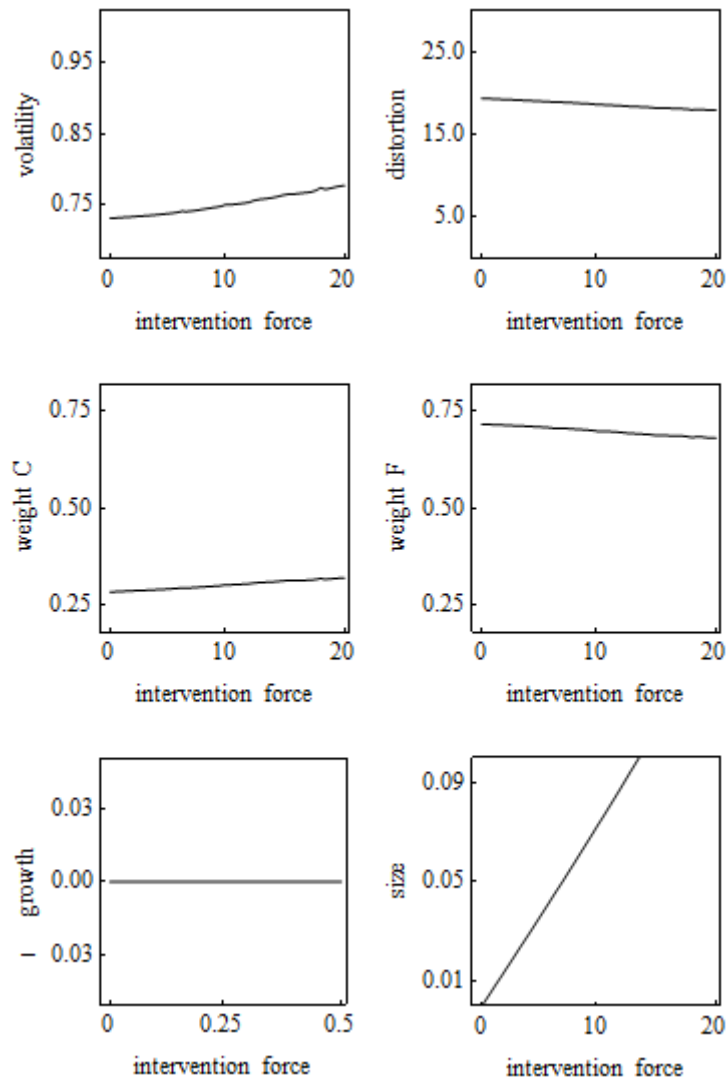


Figure 7: Some effects of leaning against the wind interventions. Parameter setting as in Figure 1. In addition, parameter f is increased from 0 to 20 and the log target rate is $P^A = 0$.

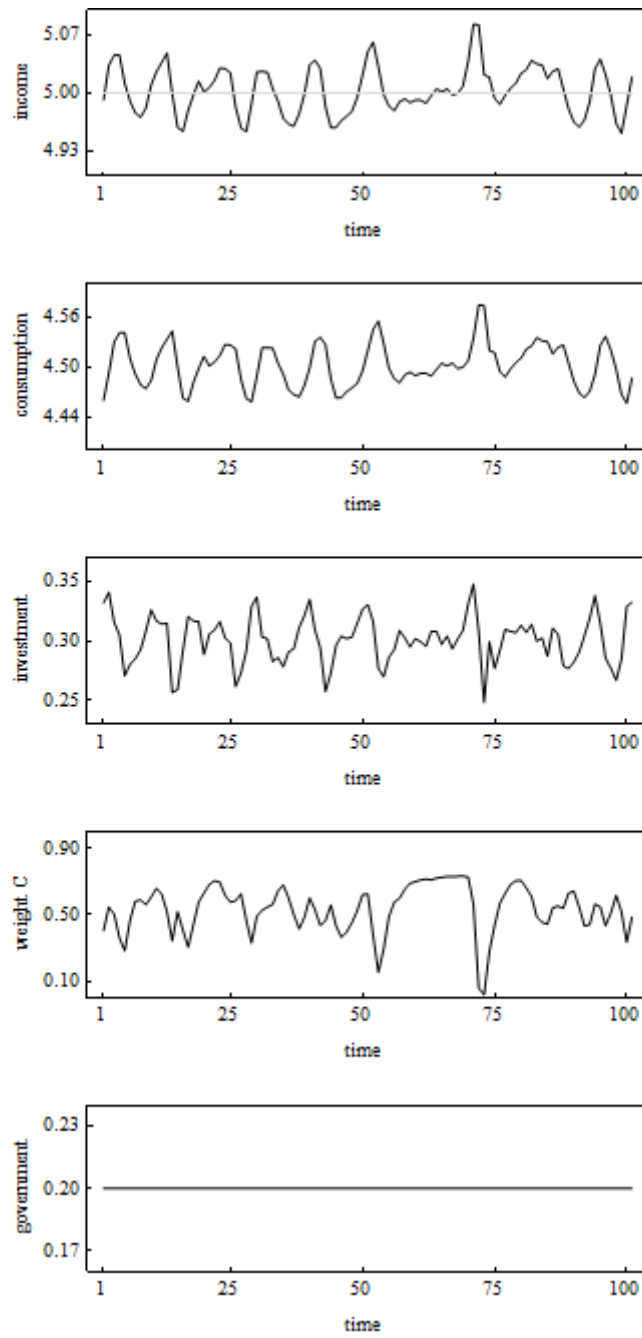


Figure 8: The dynamics of the agent-based goods market model without regulations. Parameter setting as in Section 3.

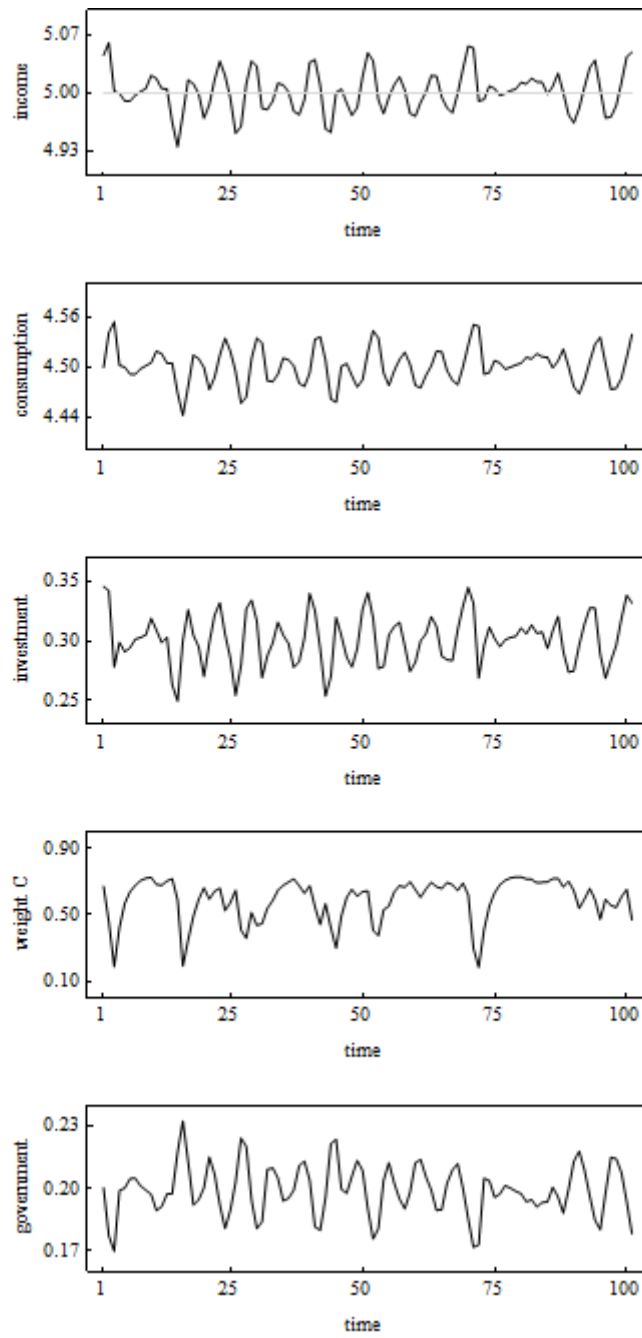


Figure 9: The dynamics of the agent-based goods market model with (unbiased) level-adjusting interventions. Parameter setting as in Figure 8. In addition, parameter $e = 0.4$ and target value of national income $Y^A = 5$.

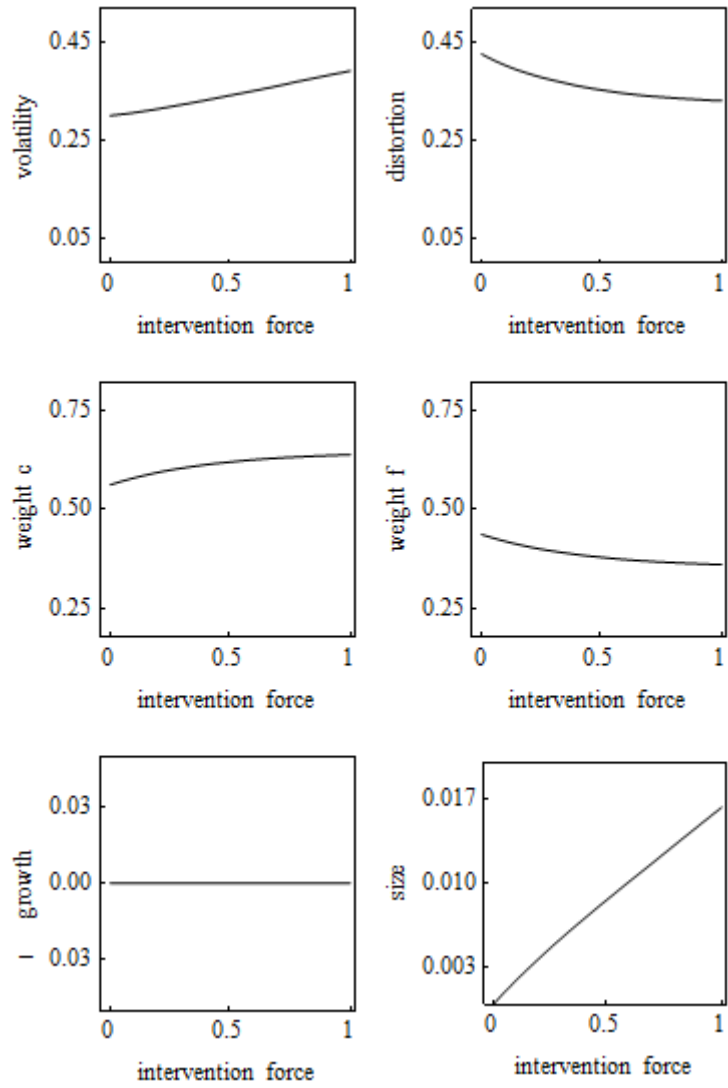


Figure 10: Some effects of (unbiased) level-adjusting interventions. Parameter setting as in Figure 8. In addition, parameter e is increased from 0 to 1 and the target value of national income is $Y^A = 5$.

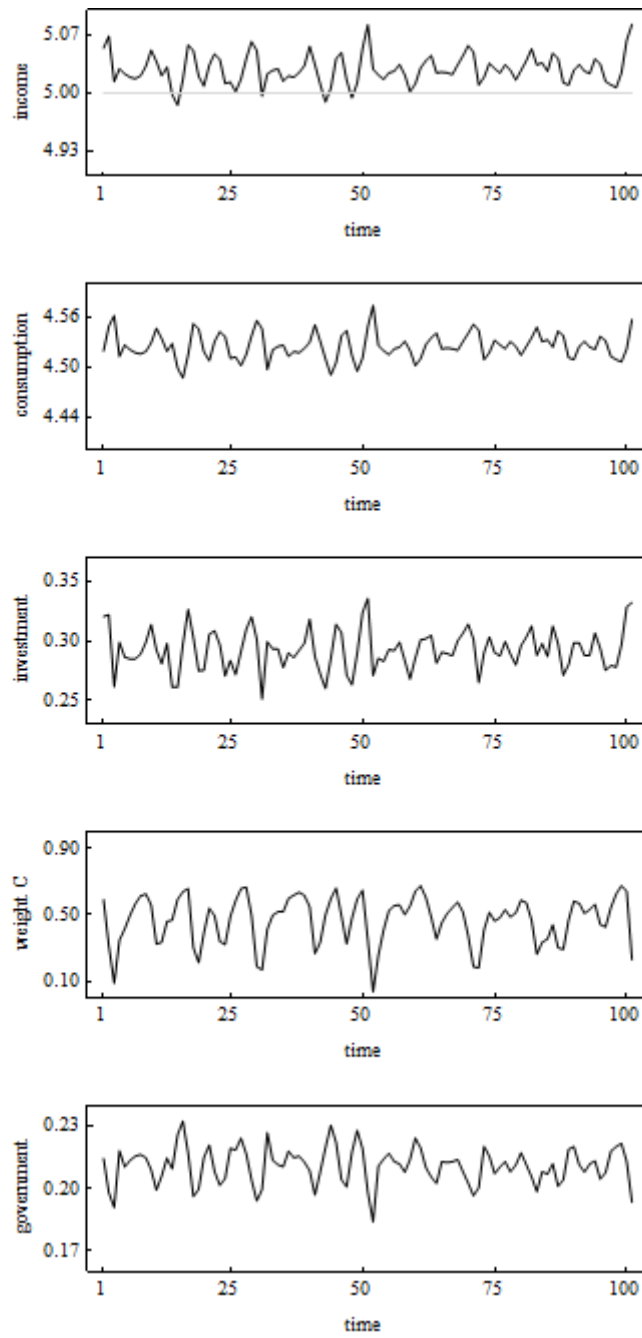


Figure 11: The dynamics of the agent-based goods market model with (unbiased) level-adjusting interventions. Parameter setting as in Figure 8. In addition, parameter $e = 0.4$ and target rate of national income $Y^A = 5.05$.

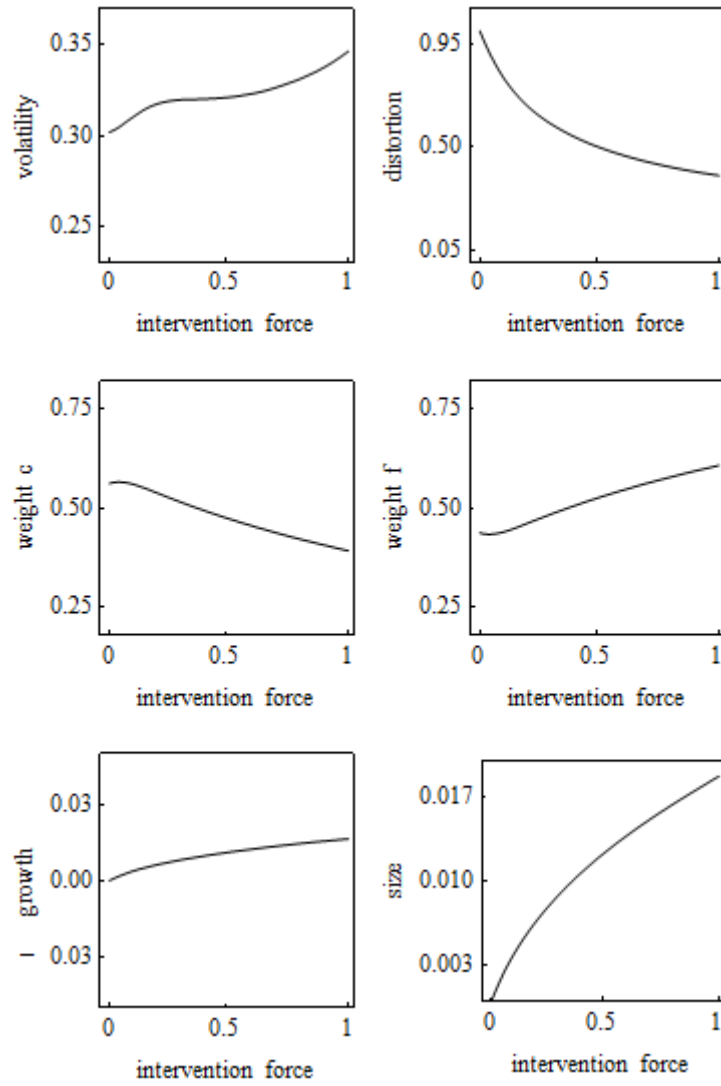


Figure 12: Some effects of (biased) level-adjusting interventions. Parameter setting as in Figure 8. In addition, parameter e is increased from 0 to 1 and the target rate of national income is $Y^A = 5.05$.

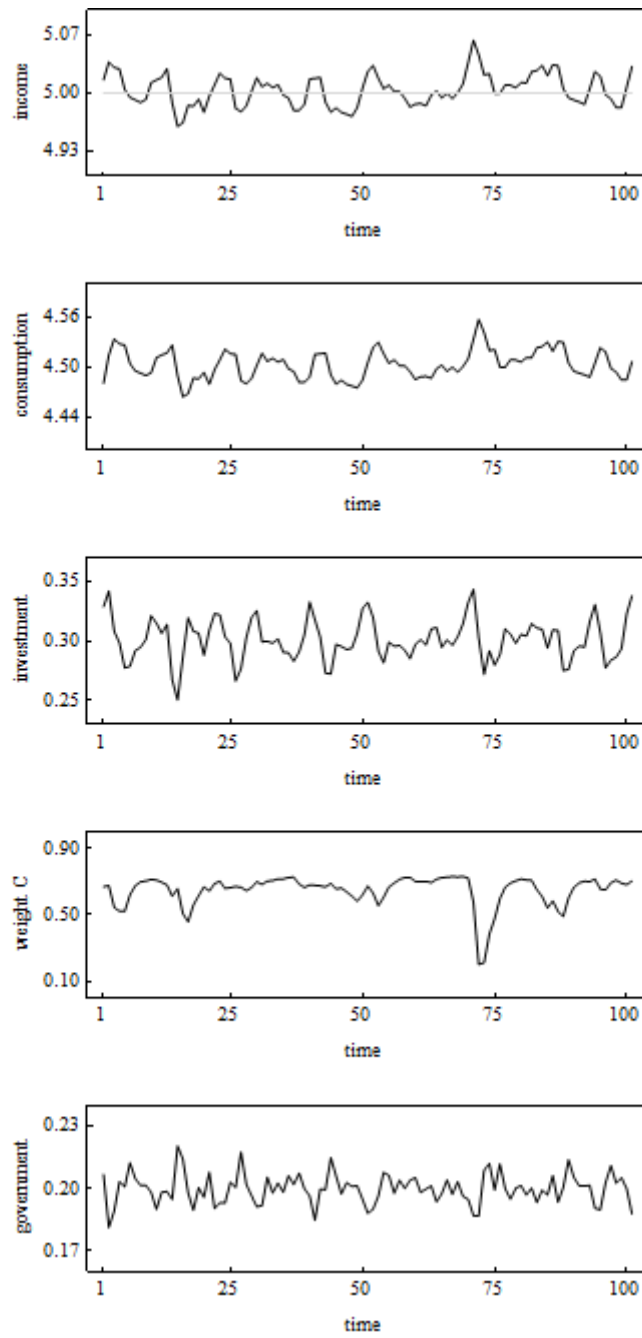


Figure 13: The dynamics of the agent-based goods market model with trend-offsetting interventions. Parameter setting as in Figure 8. In addition, parameter $f = 0.5$ and target rate of national income $Y^A = 5$.

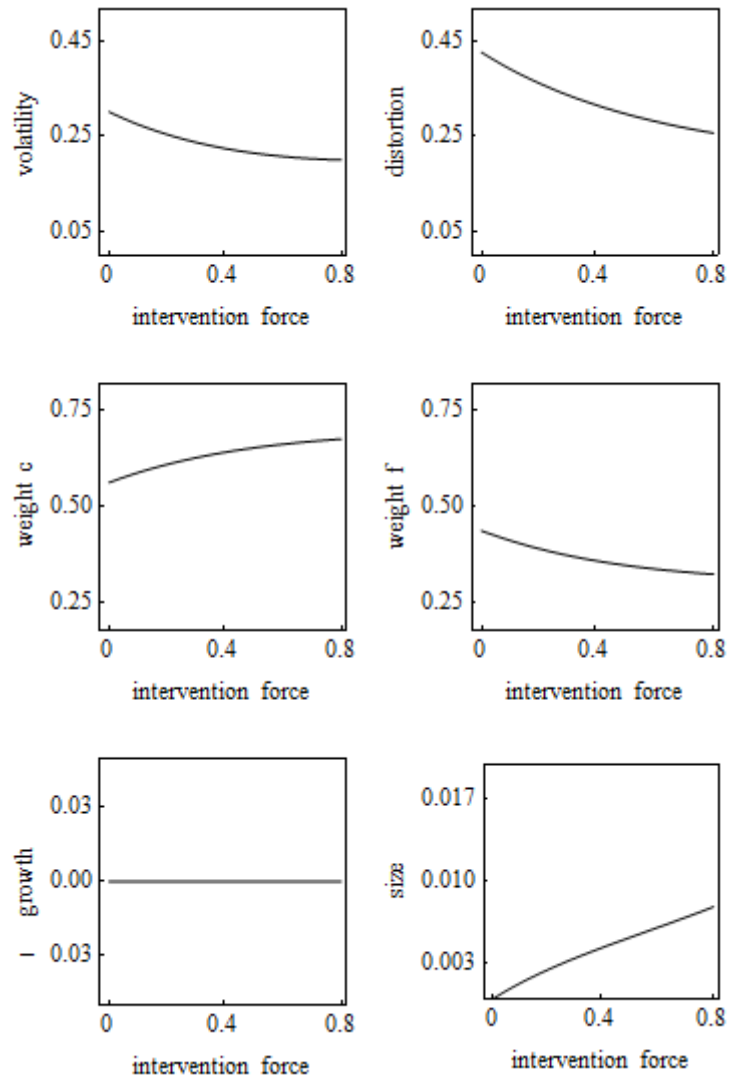


Figure 14: Some effects of trend-offsetting interventions. Parameter setting as in Figure 8. In addition, parameter f is increased from 0 to 0.8 and the target rate of national income is $Y^A = 5$.

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