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REGULAR ARTICLE

Transaction taxes, greed and risk aversion in an agent-based financial market model

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Abstract Recent agent-based financial market models came to the result that taxing financial transactions does not per se increase financial stability and that the response of volatility and misalignments to rising tax rates seem to be *u*-shaped. Moreover, greed and the risk appetite of traders are often blamed for financial instability and there is no evidence how greed and risk aversion affect the effectiveness of regulations in financial markets. We aim to add to this gap in the literature by analyzing how the effectiveness of transaction taxes depend on different behavioral patterns within an agent-based framework. Our simulations indicate that a tax rate of 0.1% demarcates the stabilizing tax regime from the destabilizing one. We figure out that transaction taxes are less effective, either when chartists trade more aggressively, fundamentalists trade less aggressively, agents switch more frequently between trading strategies or only have short memory in their fitness measures. Lower risk aversion of agents, however, makes higher tax rates more effective as indicated by a flatter volatility response curve. We conclude that additional regulations should concentrate on the traders' responsibilities for their risk-exposure.

Keywords Agent-based financial market models · Regulations of financial markets · Financial stability · Monte carlo analysis · Technical and fundamental analysis

JEL Classification C15 · D84 · G01 · G15 · G18

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1 Introduction

Financial instability is often said to be caused by greed and the risk appetite of market participants. Newspaper articles which comment financial market outcomes are full of phrases like ”bull markets” or ”hot spots” during financial bubble periods. Westerhoff (2004a) suggest that agents' greed and fear has important implications for asset price dynamics. He notes that agents optimistically believe in booming markets, while panic dominates when prices change apruptly. Menkhoff and Schmidt (2005) find in a questionaire survey among fund managers that buy-&-hold traders behave fundamentally oriented and risk averse, while momentum traders are less risk-averse and follow aggressively the trend. We should expect that the higher risk-aversion limits the stabilizing impact of fundamentalists, while less risk-aversion enhances the destabilizing impact of chartists. Thereby greed and risk-aversion might affect the effectiveness of regulations through the stabilizing behavior of fundamentalists. Up to now, there is less evidence how financial regulations work under different behavioral patterns. The scope of this paper is to fill this gap in the literature by analyzing how traders' risk aversion and aggressiveness affects the ability of transaction taxes to stabilize financial markets within an agent-based model.[1]

Up to now, there is a growing body of literature which analyzes the effectiveness of transaction taxes in agent-based financial market models (Westerhoff 2003a, 2009; Westerhoff and Dieci 2006; Pelizzari and Westerhoff 2007; Demary 2008, 2010). Lux (2009a) highlights that the success of agent-based models in replicating empirical stylized facts makes them preferable tools for economic policy analysis.[2] Westerhoff (2008) highlights the following advantages of agent-based policy analysis: (i) the researcher is able to generate as much data as needed, (ii) is able to measure all variables precisely, (iii) is able to control any exogeneous events, (iv) is able to replicate the policy experiment under the same conditions, and (v) the researcher is able to measure the behavior of the artificial agents. The last point is crucial for understanding the coordination of individual decisions which determine the aggregate behavior of the system. Demary (2008, 2010) highlights that agent-based models are preferable tools for analyzing financial regulations, since they meet the necessary requirements and assumptions for performing these policy experiments: (i) these models distinguish between different trading strategies, (ii) traders are allowed to change their trading strategy or leave the market in response to regulations, (iii) the models are based on realistic behavioral assumptions, (iv) are able to generate realistic asset price dynamics, and (v) might therefore be able to generate realistic policy implications as also highlighted in Lux (2009a).

[1] Keynes (1936) blamed traders' *“animal spirits”* for the occurance of bubbles and crashes in asset prices. He proposed to tax financial markets in order to reduce speculative trading. His argument was concretized by Tobin (1978), who proposed to tax international capital flows.

[2] The effectiveness of central bank interventions were analyzed with agent-based models in Westerhoff (2001, 2008) and Wieland and Westerhoff (2005). Weidlich and Veit (2008) use agent-based models for analyzing regulations in the electricity market, while Haber (2008) applies an agent-based model for monetary and fiscal policy analysis. Westerhoff (2003b, 2006, 2008) analyze the effectiveness of trading halts in financial markets.

Most studies that analyze the effectiveness of financial market taxes within agent-based models figure out that taxing financial transactions is not stabilizing per se. Westerhoff (2003a, 2008) finds that small transaction taxes have the potential to stabilize financial markets, while higher tax rates will destabilize the market. Demary (2010) introduces additional longer term traders into the model of Westerhoff (2008) and replicates this u-shaped response of mispricings to taxation. His simulations reveal that under sufficiently small tax rates traders abstain from short-term trading in favor of longer term investment horizons. Similar to Westerhoff (2003a, 2008), mispricings increase when the tax rate exceeds a certain threshold. This outcome emerges, since taxation reduces short-term fluctuations and longer lasting trends emerge. As a result, the longer term fundamentalist rule becomes unpopular and the longer term chartist rule rises in popularity, which leads to a destabilization of the artificial financial market. Westerhoff and Dieci (2006) analyze financial market taxes when traders are allowed to trade in two different markets. Their simulations reveal that the volatility in the taxed market will decline, while the volatility in the untaxed market will increase, since the trend-chasing trading rules are more profitable in untaxed markets. However, the volatility in both markets will decline when the tax is levied onto both markets. Pelizzari and Westerhoff (2007) show that transaction taxes work in a dealership market since liquidity is provided by specialists, while they are not effective in continuous double auction markets since the reduction in market liquidity increases the market impact of orders.

Most studies do not analyze how the effectiveness of policy measures depend on behavioral patterns of traders. Therefore, we introduce financial market taxes into the model proposed by DeGrauwe and Grimaldi (2006), which explicitly assumes risk averse traders. We expand the original model by structural stochastic volatility as proposed by Franke and Westerhoff (2009), Westerhoff (2008) and Westerhoff and Dieci (2006). As Franke and Westerhoff (2009) note, structural stochastic volatility is an important generator of volatility clusters. This expansion leads to more realistic daily fluctuations of returns compared to the original model formulation. Within our analysis we aim at figuring out which behavioral patterns make taxation more effective as indicated by a change in the shape of the u-shaped volatility and misalignment response curves to taxation.

Within the analysis the following results emerge: (i) The tax rate 0.1% demarcates the stabilizing tax regime from the destabilizing tax regime. (ii) The volatility and misalignment response curves become flatter the less risk averse agents are. (iii) More aggressive fundamental trading makes taxes more effective, while (iv) more aggressive chartists makes them less effective. (v) The more agents switch to the most profitable trading rule in response to changes in the performance measures, the less effective is taxation. (vi) Longer memory in the performance measures makes low transaction taxes more effective as indicated by a flatter volatility response curve. We conclude that additional regulations should concentrate on the traders' responsibilities for their risk-exposure.

The remainder of this paper is structured as follows. Section 2 presents the model, where Sect. 3 analyses some properties of the model. Section 4 deals with calibration, validation and the simulation design. Section 5 presents the results of the policy analysis, while Sect. 6 ends this paper with conclusions and outlook.

2 The artificial financial market

The artificial financial market is modeled in spirit of DeGrauwe and Grimaldi (2006) who assume risk averse traders.[3] In contrast to the original formulation, we abstract from the time varying risk evaluation of traders and expand the model to a structural stochastic volatility model (SSV) as proposed by Westerhoff (2008) and Franke and Westerhoff (2009). As Franke and Westerhoff (2009) note, SSV might be a relevant generator of volatility clusters. Under the introduction of SSV the DeGrauwe and Grimaldi (2006) model is able to generate more realistic daily fluctuations of asset prices compared to the original formulation even when we abstract from the time-varying risk-evaluation of traders. The rationale for this restiction is that although we want the model to be a good description of observed data, we wish to keep it sophisticated simple as well in order to understand easier how financial regulations work within the model.[4]

The model consists of the following building blocks

- (i) an exogeneous fundamental exchange rate,
- (ii) traders who choose between a fundamental and a trend-chasing trading rule, who are allowed not to trade, when the transaction costs associated with trading in the foreign exchange market are higher compared to the returns of trading,
- (iii) an evolutionary process that determines the popularity of the trading rules according to their past performance,
- (iv) market demand that meets market supply for determining the value of the exchange rate, and
- (v) a policy maker who sets the currency transaction tax rate.

2.1 Portfolio allocation

Following DeGrauwe and Grimaldi (2006) we assume that traders are myopic one-period investors who only care about the return and the risk of their investment. Traders allocate their investment positions by investing in either a riskless domestic asset with return r or into a risky foreign asset with return r^*. The foreign asset is risky due to fluctuations in the exchange rate s_t. Agents have to buy foreign currency, when they decide to invest into the foreign asset. They determine their demand for the foreign currency d_t^i by maximizing their mean-variance-utility

$$\mathcal{U}\left(W_{t+1}^i\right) = \mathcal{E}_t^i\left(W_{t+1}^i\right) - \frac{\mu}{2}\mathcal{V}\left(W_{t+1}^i\right) \tag{1}$$

[3] Influencial contributions to agent-based financial market models are surveyed in Westerhoff (2009), Hommes (2006), LeBaron (2006) and Lux (2009a).

[4] The time-varying risk-evaluation (TVRE) of traders as well as the heterogeneity in the variation of the trading rules of chartists and fundamentalists (which leads to SSV) are both generators of volatility clustering. When I abstract from the TVRE and only use the SSV, volatility clusters and slowly declining autocorrelations of absolute returns remain. However, when I abstract from SSV and only use the TVRE, the model produces less persistent autocorrelations compared to empirical data. I conclude that SSV is the more important generator of volatility clustering. Moreover, this simplification is not crucial for the models ability to explain stylized facts nor for the implications of the policy analysis.

subject to their wealth contraint

$$\mathcal{E}_t^i W_{t+1} = (1+r)W_t + (1+r^*)\mathcal{E}_t^i s_{t+1} d_t^i - (1+r)s_t d_t^i. \tag{2}$$

The agent's wealth at time $t+1$ is denoted by W_{t+1}^i and consists of the compounded wealth endowment from the previous period $(1+r)W_t$, the investment in the foreign asset $(1+r^*)\mathcal{E}_t^i s_{t+1} d_t^i$ and the domestic component $-(1+r)s_t d_t^i$. When the agent borrows money in his or her home country for an investment into the foreign asset, then $d_t^i > 0$, since he or she needs to convert the domestic money into foreign currency, while $d_t^i < 0$ indicates that the agent borrows money abroad, which he or she has to convert to domestic currency for investing it into the home country. Since d_t^i is the demand for foreign currency, the exchange rate s_t is given as the price of the foreign currency in domestic currency units. Note, that DeGrauwe and Grimaldi (2006) assume agents to be bounded rational. Hence, $\mathcal{E}(.)$ and $\mathcal{V}(.)$ are not the objective expectation and variance operators based on objective probabilities, but they are the individual traders subjective expectations and the subjective variance assessments based on bounded-rational rules of thumb. By solving this portfolio allocation problem we arrive at the following demand for foreign currency

$$d_t^i = \frac{(1+r^*)\mathcal{E}_t^i(s_{t+1}) - (1+r)s_t}{\mu \mathcal{V}_t^i(s_{t+1})}. \tag{3}$$

Typically for utility functions with constant absolute risk aversion the demand for the risky asset does not depend on initial wealth W_t, is rising in the return of the risky asset and declining in the risk of the asset. Note, that μ is the degree of risk aversion, a parameter crucial for our analysis. Since we abstract from interest rate risk, we set following DeGrauwe and Grimaldi (2006) the interest rates to zero ($r = r^* = 0$). Under this restriction we arrive at a demand function, which is in line with the ones used in Westerhoff (2003a,b,c, 2004b) and Manzan and Westerhoff (2005)

$$d_t^i = \frac{\mathcal{E}_t^i(s_{t+1}) - s_t}{\mu \mathcal{V}_t^i(s_{t+1})}. \tag{4}$$

Traders buy foreign currency when they expect the exchange rate to rise ($\mathcal{E}_t^i(s_{t+1}) > s_t$), while they sell foreign currency when they expect the exchange rate to decline in the future ($\mathcal{E}_t^i(s_{t+1}) < s_t$). However, these demands are augmented by risk aversion in the DeGrauwe and Grimaldi (2006) model. This means, that the demands will be smaller in absolute value when there is more risk associated with trading in the foreign exchange market.

Buy or sell orders generate transaction costs $\tau s_t d_t^i$, since the policy maker levies a proportional transaction tax τ in spirit of the one proposed by Tobin (1978). A round trip of investing in the foreign country and consuming the profit in the home country leads to the following profit after taxes (see Westerhoff 2008 and Demary 2010)

$$\tilde{\pi}_t^i = (s_t - s_{t-1})d_{t-1}^i - \tau(s_t + s_{t-1})|d_{t-1}^i|. \tag{5}$$

The first part of this formulation is the return of buying (selling) foreign currency at s_{t-1} and selling (buying) it at s_t, while the last part is the transaction costs associated with these two transactions. When agents face transaction costs they will only adjust their portfolios, when the profit from adjusting the portfolio is higher compared to the transaction costs

$$x_t^i = \begin{cases} d_t^i, & \text{if } (s_t - s_{t-1})d_{t-1}^i > \tau(s_t + s_{t-1})|d_{t-1}^i|; \\ 0, & \text{otherwise}. \end{cases} \tag{6}$$

Hence, the transaction tax creates a neutral band around the no-arbitrage condition $(s_t - s_{t-1})d_{t-1}^i = 0$, which is in line with the literature on financial market taxes.

2.2 Agents' forecasting rules

The traders' forecasting rules are modeled following the literature on agent-based financial market models. These trading rules are based on empirical evidence from survey studies among market participants which were originally performed by Taylor and Allen (1992).[5] One result is that professional traders either rely on trading rules that take explicitly economic fundamentals into account, while others use chartists techniques that rely on trends or other patterns in past asset prices and ignore economic fundamentals. As already noted, Menkhoff and Schmidt (2005) find that buy-&-hold traders behave fundamentally oriented and risk averse, while momentum traders are less risk averse and follow aggressively the trend.

The fundamentalist forecasting rule expects that the exchange rate s_t will revert to the fundamental exchange rate s_t^f in the distant future, with a rate of error-correction of $\kappa_F \cdot 100\%$.

$$\mathcal{E}_t^F(\Delta s_{t+1}) = \kappa_F \left(s_{t-1}^f - s_{t-1} \right) + \sigma_F \varepsilon_t^F, \quad \text{with } \varepsilon_t^F \sim \mathcal{N}(0,1). \tag{7}$$

The random disturbance ε_t^F can be interpreted as the fundamentalists' misperception of the fundamental value (Westerhoff 2008). Its volatility σ_F accounts for the uncertainty associated with using this expectational rule. This assumption is based on the fact that neither the fundamental value nor the reversion speed of the exchange rate toward this fundamental can be inferred without observational error.

Chartists believe that the past trend segment $s_{t-1} - s_{t-2}$ can be extrapolated into the future

$$\mathcal{E}_t^C(\Delta s_{t+1}) = \kappa_C(s_{t-1} - s_{t-2}) + \sigma_C \varepsilon_t^C, \quad \text{with } \varepsilon_t^C \sim \mathcal{N}(0,1). \tag{8}$$

The parameter κ_C is the strength of the trend-extrapolation. For $\kappa_C > 0$ this rule is trend-chasing, while chartists act as contarians for $\kappa_C < 0$. It can also be interpreted as the chartists' aggressiveness. The random disturbance ε_t^C can be interpreted as a

[5] Menkhoff and Taylor (2007) give an overview over these studies and their key results.

deviation from this strict deterministic rule. The volatility parameter σ_C accounts for the variety of chartist rules (Westerhoff 2008).

The volatilities σ_C and σ_F are crucial for the SSV mechanism.

2.3 Risk evaluation

DeGrauwe and Grimaldi (2006) assume agents to calculate a moving average of past forecast errors in order to account for the uncertainty associated with their trading rule

$$\mathcal{V}_t^i(s_{t+1}) = \omega + \alpha(s_t - \mathcal{E}_{t-1}^i(s_t))^2 + \beta\mathcal{V}_{t-1}^i(s_t). \tag{9}$$

When agents assume a constant risk, as in Brock and Hommes (1998), then $\alpha = \beta = 0$, We assume this restriction, since we concentrate on SSV as a generator for volatility clusters.

2.4 Evaluation of trading rules

Traders are allowed to change their trading rules when other rules are more successful compared to theirs. This mechanism was originally proposed by Brock and Hommes (1998). Following Westerhoff (2008) and Demary (2010) we assume the following fitness measures

$$\pi_t^i = (s_t - s_{t-1})x_{t-1}^i - \tau(s_t + s_{t-1})|x_{t-1}^i| + \theta\pi_{t-1}^i. \tag{10}$$

The memory parameter θ can often be found in agent-based models (see Westerhoff 2008; Westerhoff and Dieci 2006). It measures how strong agents discount past profits for strategy selection. When $\theta = 0$, then only todays profits determine the popularity of the trading strategies, while for $\theta = 1$ all past profits will be considered.

Following Westerhoff (2003a, 2008) and Demary (2010) we assume that traders can choose between using the chartist trading rule, the fundamentalist trading rule or they abstain from trading. The last possibility is crucial when traders act under transaction costs. When the transaction costs of trading in the foreign exchange market are higher compared to the return of trading then traders decide to stay inactive as already highlighted in the subsection before. Brock and Hommes (1998) suggest the percentage fractions of traders to be determined by the discrete choice model proposed by Manski and McFadden (1981). Hence, the percentage fraction of traders using the fundamentalist rule is determined as

$$w_t^F = \frac{\exp\left\{\gamma\pi_t^F\right\}}{1 + \exp\left\{\gamma\pi_t^F\right\} + \exp\left\{\gamma\pi_t^C\right\}}, \tag{11}$$

the percentage fraction of traders using the chartist rule is

$$w_t^C = \frac{\exp\left\{\gamma\pi_t^F\right\}}{1 + \exp\left\{\gamma\pi_t^F\right\} + \exp\left\{\gamma\pi_t^C\right\}}, \tag{12}$$

while the percentage fraction of traders, who abstain from trading is given by

$$w_t^I = \frac{1}{1 + \exp\left\{\gamma \pi_t^F\right\} + \exp\left\{\gamma \pi_t^C\right\}}, \tag{13}$$

since the profit generated by abstaining from trade is zero by construction. The parameter γ can be interpreted as the intensity of choice parameter. The higher γ the more agents switch to the trading rule which was the most profitable one in the past. For $\gamma = 0$ we have the special case of constant population fractions, while for $\gamma = \infty$ all agents switch to the most profitable trading strategy.

2.5 Market equilibrium

Market demand for foreign currency X_t is given by the sum over all individual demands x_t^i multiplied by the number of agents n_t^i, who use one of the possible trading strategies

$$X_t \equiv n_t^C x_t^C + n_t^F x_t^F + n_t^I x_t^I. \tag{14}$$

Here n_t^C is the number of agents, who use the chartist trading rule to determine their demand, n_t^F is the number of agents who use the fundamentalist rule to determine their demand, while n_t^I is the number of inactive agents. Since these agents abstain from trading, their demand is zero. Since DeGrauwe and Grimaldi (2006) normalize the supply of foreign assets to zero, the market clearing condition is given by

$$n_t^C x_t^C + n_t^F x_t^F = 0. \tag{15}$$

The rationale for setting the supply for foreign currence to zero is that we abstract from central bank interventions which are beyond the scope of this paper.

We follow the derivation of the model explained in DeGrauwe and Grimaldi (2006). By dividing through the total number of agents $N \equiv n_t^C + n_t^F + n_t^I$ and by defining the percentage fractions as $w_t^i \equiv n_t^i / N$, we arrive at

$$w_t^C x_t^C + w_t^F x_t^F = 0. \tag{16}$$

Inserting the traders' demand functions results in

$$w_t^C \cdot \frac{s_{t-1} + \mathcal{E}_t^C(\Delta s_{t+1}) - s_t}{\mu \mathcal{V}_t^C(s_{t+1})} + w_t^F \cdot \frac{s_{t-1} + \mathcal{E}_t^F(\Delta s_{t+1}) - s_t}{\mu \mathcal{V}_t^F(s_{t+1})} = 0. \tag{17}$$

Dividing by $\left\{w_t^C / \mathcal{V}_t^C(s_{t+1}) + w_t^F / \mathcal{V}_t^F(s_{t+1})\right\}$ yields

$$s_t = s_{t-1} + \Theta_t^C \mathcal{E}_t^C(\Delta s_{t+1}) + \Theta_t^F \left(\mathcal{E}_t^F(\Delta s_{t+1})\right), \tag{18}$$

where we define the risk-adjusted population fractions in line with DeGrauwe and Grimaldi (2006) as

$$\Theta_t^C \equiv \frac{w_t^C / \mathcal{V}_t^C(s_{t+1})}{w_t^C / \mathcal{V}_t^C(s_{t+1}) + w_t^F / \mathcal{V}_t^F(s_{t+1})} \tag{19}$$

$$\Theta_t^F \equiv \frac{w_t^F / \mathcal{V}_t^F(s_{t+1})}{w_t^C / \mathcal{V}_t^C(s_{t+1}) + w_t^F / \mathcal{V}_t^F(s_{t+1})}. \tag{20}$$

Inserting the fundamentalist and chartist forecasting models yields

$$s_t = s_{t-1} + \Theta_t^C \left(\kappa_C(s_{t-1} - s_{t-2}) + \sigma_C \varepsilon_t^C\right) + \Theta_t^F \left(\kappa_F(s_{t-1}^F - s_{t-1}) + \sigma_F \varepsilon_t^F\right) + \sigma \varepsilon_t^S, \tag{21}$$

where $\varepsilon_t^S \sim \mathcal{N}(0, 1)$ is a constant fraction of noise traders in the market, which ensure a minimum fraction of liquidity in the market for the case that a large fraction of chartists and fundamentalists abstain from trading under transaction taxes. Rearranging this equation results in

$$s_t = s_{t-1} + \Theta_t^F \kappa_F \left(s_{t-1}^F - s_{t-1}\right) + \Theta_t^C \kappa_C (s_{t-1} - s_{t-2}) + \sigma_t \varepsilon_t^S \tag{22}$$

$$\sigma_t \equiv \sigma + \Theta_t^F \sigma_F + \Theta_t^C \sigma_C. \tag{23}$$

This model is characterized by SSV, which is according to Franke and Westerhoff (2009) an important generator of volatility clustering. The mean value dynamics (22) are characterized by a centrifugal component $\kappa_C(s_{t-1} - s_{t-2})$ and a centripetal component $\kappa_F(s_{t-1}^F - s_{t-1})$ (see Lux 2009a,b). The centrifugal component is caused by the trend-chasing behavior of chartist traders, while the centripetal force is caused by the stabilizing behavior of fundamentalists. The exchange rate dynamics is characterized by an on-off-intermittency due to fluctuations in the population weights Θ_t^F and $\Theta_t^C = 1 - \Theta_t^F$ (see Lux and Marchesi 2000). Thus, the exchange rate s_t deviates from its fundamental value s_t^F and a speculative bubble emerges when Θ_t^C is large, while the exchange rate will be attracted by its fundamental value, when Θ_t^F is large. These fluctuations in the population weights also lead to volatility clusters due to the SSV formulation of the volatility dynamics (23), when the variability in chartist rules is larger compared to the variability in fundamentalist rules $\sigma_C > \sigma_F$. When Θ_t^C is large, the market is in a high volatility state, while the market will be in a low volatility state, when Θ_t^F is large. By affecting the population weights, the transaction tax rates has effects onto the mean value dynamics as well as onto the volatility dynamics.

3 The fundamental equilibrium

For analyzing the long-term properties of the model we follow the derivations in Westerhoff and Dieci (2006) and concentrate on the deterministic skeleton of the model. Hence, we set all shocks to zero. The long-term solution is given when

$$\left(s_{t-1}, s^F, x^i_{t-1}, w^i_{t-1}, \pi^i_{t-1}\right) = \left(s_t, s^F, x^i_t, w^i_t, \pi^i_t\right) = \left(\overline{s}, s^F, \overline{x^i}, \overline{w^i}, \overline{\pi^i}\right) \tag{24}$$

for $i \in \{C, F, I\}$.

Within the long-term fundamental steady-state $s_{t-1} = s_t = \overline{s} = s^F$ traders demand for foreign currency will be zero

$$\overline{x^C} = \overline{x^F} = \overline{x^I} = 0, \tag{25}$$

and all fitness measures will be zero as well

$$\overline{\pi^C} = \overline{\pi^F} = \overline{\pi^I} = 0. \tag{26}$$

Zero fitness measures for all agents leads to a uniform distribution in the popularity of all three trading rules

$$\overline{w^C} = \overline{w^F} = \overline{w^I} = \frac{1}{3}, \tag{27}$$

which leads to

$$\overline{\Theta^C} = \overline{\Theta^F} = \frac{1}{2}. \tag{28}$$

Comparable results can often be found in chartist-fundamentalist models (DeGrauwe and Grimaldi 2006; Westerhoff 2008; Westerhoff and Dieci 2006).

Stability properties for a comparable fundamental steady-state can be found in Westerhoff and Dieci (2006).

4 Calibration, validation and simulation design

4.1 Calibration

Before we start the simulation of the model and the policy analysis, we have to find resonable values for the model's parameters. Most parameter values are in the range as the ones used in Westerhoff (2008) and Demary (2010), which are chosen such that the model is able to match numbers and statistics of real world financial market data.[6] Westerhoff (2008) and Demary (2010) assume chartists' and fundamentalists' aggressiveness as $\kappa^C = \kappa^F = 0.04$. Hence, chartists expect an exchange rate change of 0.04 for the next trading day in response to a past exchange rate change of 1, while fundamentalists expect an exchange rate change of 0.04 in response to a misalignment

[6] Studies in which agent-based financial market models were estimated are Gilli and Winker (2003), Westerhoff and Reitz (2003), Lux (2009b), Alfarano et al. (2005), Boswijk et al. (2007), Winker et al. (2007), Manzan and Westerhoff (2007) and Ghongadze and Lux (2009).

Table 1 Calibration of the baseline simulation

Parameter	Value	Interpretation
κ_C	0.04	Chartists' aggressiveness
κ_F	0.04	Fundamentalists' agressiveness
σ_C	0.055	Variety of chartist rules
σ_F	0.005	Variety of fundamentalist rules
γ	600	Intensity of choice
θ	0.98	Memory parameter
σ_S	0.005	Volatility of non-fundamental innovations
μ	50	Degree of risk aversion
ω	0.03	Subjective volatility estimate
s^F	10	Fundamental exchange rate

Most parameter values are chosen following the parameterization of Westerhoff (2008) and Demary (2010). All remaining parameters are given such that the model reproduces properties of real world exchange rate data quite well

of 1. The variation in the chartist trading rules $\sigma^C = 0.055$ is higher compared to the fundamentalists misperception $\sigma^F = 0.005$, in order to achieve volatility clusters through the SSV mechanism. The memory parameter $\theta = 0.98$ indicates that agents orientate on recent as well as on past performances of all trading rules. The intensity of choice parameter $\gamma = 600$ ensures that enough traders change their views of the world in response to changes in the performance measures. The agents' subjective volatility estimate $\omega = 0.03$ seems to be high, since its value is larger compared to the volatility of the exchange rate. However, this high value is necessary for the simulations to be computationally stabile and to avoid unrealistic large crashes in the exchange rate due to unrealistic high demands of chartists. Another is, that it is the compound parameter $\mu \times \omega$ that determines risk aversion and not the value of ω alone. We calibrate the risk aversion parameter $\mu = 50$ such that the simulations yield realistic return properties. The reason for this assumption is, that there is no empirical evidence on reasonable values for this parameter. The fundamental value of the exchange rate is assumed to be constant and normalized to $s^F = 10$ (Table 1).

4.2 Validation

Following Westerhoff (2008), Lux (2009a), Westerhoff and Franke (2009) and Demary (2010) we use the following validation criteria, which are based on the stylized facts of financial market data: (i) asset prices are characterized by bubbles and crashes (deviations from fundamental value), (ii) asset prices should be more volatile compared to their fundamental values (excess volatility or distortions), (iii) the return distribution should deviate from the normal distribution (excess kurtosis), (iv) absence of autocorrelation in raw returns (non-predictability of daily returns), (v) persistent and slowly decaying autocorrelations in absolute returns (volatility clustering).

There are additional stylized facts from which we abstract. We concentrate on the minimum required stylized facts, that a model should be able to match instead. Unfortunately, models with less economic structure are better in replicating stylized facts. However, we need a model with an economic foundation to do an economic policy analysis. Since the aim of this paper is not to reproduce stylized facts as precise as

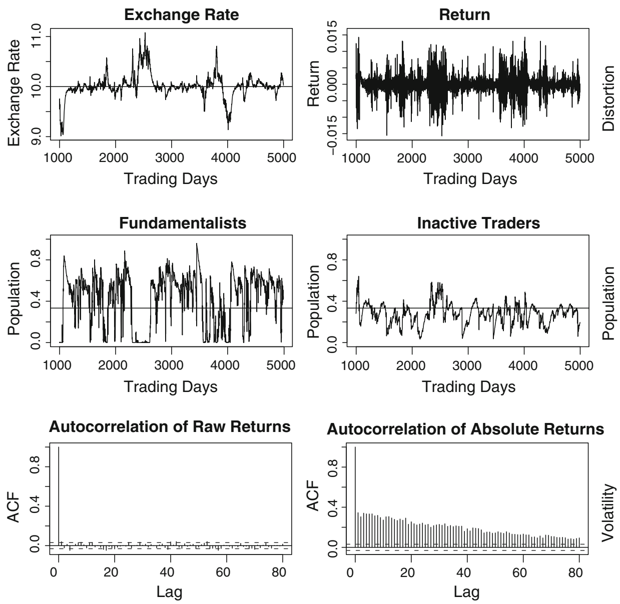

Fig. 1 Baseline simulation: no taxes levied. *Notes* The output of a typical simulation run. The underlying parameter values are those given in Table 1. Fundamental values are represented by *horizontal lines* at $\overline{s^F} = 10$ and $\overline{w^F} = \overline{w^C} = \overline{w^I} = 1/3$. Distortion is the average absolute percentage deviation of the exchange rate from its fundamental value, while volatility is the average absolute percentage time change in the exchange rate

possible, but to do an economic policy analysis within a model that is able to reproduce realistic exchange rate fluctuations, we are satisfied when our model is able to match the most relevant (or minimum required) stylized facts of financial market data. When the model is able to meet the Franke-Lux-Westerhoff validation criteria, then our model is a sufficient representation of daily foreign exchange market dynamics and we should expect to derive realistic policy implications from it.

Figure 1 shows a snapshot of a typical simulation run.[7] The first 1,000 data points were removed in order to avoid phenomena that depend on the initial conditions. The exchange rate is characterized by persistent bubbles and crashes. As can be seen in the figure, large distortions (large deviations from the fundamental value) correspond to periods with a large number of chartist traders, while periods with the exchange rate close to the fundamental value correspond to periods dominated by fundamentalist traders. The observed distortions indicates that asset prices are more volatile than their fundamental values. Another empirical fact the model is able to replicate can be inferred from the autocorrelations of raw returns and absolute returns. Raw returns are characterized by negligible autocorrelations which indicate an absence of predictability on a daily basis. The autocorrelations of absolute returns, however, are persistent and slowly decaying. This high autocorrelations in absolute returns indicate

[7] All programming and computations were done using the free open source software R (R Development Core Team 2009).

Table 2 Summary statistics: model versus data

	USD-Euro	Yen-USD	GBP-USD	USD-AusD
Mean	0.000	0.000	0.000	0.000
Volatility	0.007	0.007	0.006	0.009
Skewness	0.179	−0.509	−0.330	−0.757
Kurtosis	5.560	6.885	9.315	17.009
	Model 1	Model 2	Model 3	Model 4
Mean	0.000	0.000	0.000	0.000
Volatility	0.002	0.003	0.002	0.007
Skewness	0.000	0.000	0.000	0.000
Kurtosis	7.283	7.545	12.005	8.057

The exchange rate data are taken from the FRED2 database of the Federal Reserve Bank of St. Louis in daily frequency. The data series range from 1999-01-04 to 2009-10-09 and are available under the series-ID: DEXUSEU, DEXJPUS, DEXUSUK, DEXCAUS and DEXAUUS. Model 1 to Model 4 are characterized by different parameter sets. Model 1 represents the baseline case given in Table 1, while model 2 assumes more aggressive chartists $\kappa^C = 0.09$, model 3 assumes more aggressive fundamentalists $\kappa^F = 0.09$, while model 4 assumes variabilities in forecasting rules of $\sigma_C = 0.12$ and $\sigma_F = 0.03$. All remaining parameters are asigned to the values given in Table 1

the presence of volatility clusters. These changing periods of high an low volatility can be inferred as well by just eyeballing the time series of returns. In line with our intuition, periods of high volatility tend to correspond to periods with a large number of chartists, while periods with low volatility correspond to periods with a high dominance of fundamentalist traders.

Table 2 compares summary statistics of the model to those of US-Dollar to Euro exchange rate returns and those of the Yen—US-Dollar exchange rate, the Great Britain Pound—US-Dollar and the US-Dollar—Australian Dollar exchange rates. All four exchange rate return time series are characterized by an average daily return near zero, a standard deviation between 0.7 and 0.9% and a kurtosis between 5.6 and 17.0 which indicate that the return distribution deviates from a normal distribution. Table 2 contains summary statistics of model generated exchange rate returns of a typical simulation run for a snapshot of 6,000 artificial trading days.[8] We report summary statistics for four calibrations of the model. The model generated daily returns are as well characterized by a mean return near zero, a standard deviation of 0.2–0.3% and a kurtosis in the range of 7.3–13.1 indicating deviations from the normal distribution. In contrast to the empirical returns, we find a skewness of zero in the artificial return distributions. The reason lies in the fact that we abstract from persistent interest rate differentials and central bank interventions, which can cause the skewness in the empirical return distributions. The volatility of models 1–3 are smaller compared to the empirical volatility, while model 4 is able to mimick the empirical volatility. However, model 4 assumes a higher variation of the chartists' and fundamentalists'

[8] Actually, we simulated 7,000 trading days from which we skipped the first 1,000 in order to avoid artefacts that depend on initial conditions.

trading rules ($\sigma_C = 0.12$ and $\sigma_F = 0.03$) as applied in the literature (Westerhoff 2008; Demary 2010). However, we perform the policy analysis under the parameterization of model 1, since this parameterization is more common in the literature. One should keep in mind that results only apply to the 1/3 of actual volatility which model 1 mimicks. However, we perform additional simulations under model 4, which produces higher volatility. Since volatility has an impact on the decisions of risk averse agents, the implications of the model with taxes might change under higher volatility. Therefore, we discuss the differences between the results of model 1 and model 4 at the end of Sect. 5.

4.3 Simulation design

Westerhoff (2008) lists advantages of agent-based policy analysis which apply to our experiments in the following way:

(i) We choose a simulation horizon of 7,000 artificial trading days, where we skip the first 1,000 data points since they are biased by fluctuations that depend on the chosen initial conditions. We calculate numbers and statistics over 6,000 trading days and present the variation in these numbers and statistics over the 50 independent simulation runs in box plots.[9] Although these box plots are more difficult to interpret compared to just average properties over 50 simulation runs, they deliver useful information about the variation of the model's properties for different simulation runs.

(ii) Westerhoff (2008) also highlights that we are able to measure all variables precisely during our simulations like the fundamental value and the decisions of agents.

(iii) Westerhoff (2008) notes that the researcher is able to account for all exogenous shocks. Within our simulations we introduce the shocks we already highlighted in the description of the model. We do not introduce other exogenous events like a large drop in the fundamental value (e.g. a big recession) or large non-fundamental innovations (e.g. panic). The reason is that we want to analyze the effectiveness of financial market taxes during "normal" trading days.

(iv) Following Demary (2010) we perform the simulations under the same conditions (the same seed of random variables), but under different tax rates. Simulations for each value of the currency transaction tax are based on the same seed of $50 \times 6{,}000 = 300{,}000$ random numbers.

The policy analysis should give us more insights in how greed and risk aversion affect the effectiveness of financial market taxes. Therefore, we have to vary the following model parameters:

(a) Transaction tax rate.

(b) Risk aversion: A large value of μ indicates that the agent is more risk averse. However, we are only able to measure constant absolute risk aversion. This means

[9] The box plots indicate the median over 50 simulation runs, the first and the third quartile. The whiskers indicate the most extreme points which are in a range of 1.5 from the box, while outliers are highlighted as dots.

that the degree of risk aversion does not depend on the agent's wealth. However, more complicated utility functions are neccessary for analyzing decreasing or increasing absolute risk aversion.

(c) Greed and aggressiveness: We define a greedy or aggressive agent as one, who has a higher aggressiveness parameter either as a chartist (κ_C) or as a fundamentalist (κ_F) or the agent's response to changes in profits (γ) is high. In more detail, when a chartist is greedy, he or she expects a stronger trend compared to a less greedy chartist and therefore places larger orders. A greedy fundamentalist expects the exchange rate to revert faster to its fundamental value and therefore places larger orders compared to a less greedy fundamentlist. Moreover, a greedy agent switches more frequently between different trading rules in order to increase his or her profits.

4.4 Policy evaluation

Westerhoff (2003a, 2008) suggests the following market (in-)efficiency measures for evaluating the effectiveness of policy measures:

(i) volatility, defined as the average absolute percentage change in the asset price.
(ii) distortion, defined as the average absolute deviation of the asset price from its fundamental value, which measures the degree of excess volatility.
(iii) Westerhoff (2008) and Demary (2008) suggest to analyze the change in the average percentage fraction of trading rules used by agents as a measure of the change in traders' behavior in response to policy measures, while
(iv) Demary (2008, 2010) suggests to use the change in the kurtosis of the return distribution as a measure of catastrophic risks caused by large outliers. There are better measures for the tail behavior of the distribution of returns like the Hill estimator for the tail index (Lux and Ausloos 2002). However, the kurtosis is a statistic which is very sensitive to outliers. Hence, although not measuring tail behavior it might be a good statistic to measure the occurance of extreme events directly, like a crash for example.

5 The effectiveness of transaction taxes

5.1 Simulation runs under taxation

Stabilizing Tax Regime: Fig. 2 shows the model outcome of a typical simulation run under a tax rate of 0.1%. Under this tax rate all chartists abstain from trading, while the number of fundamentalists fluctuates around 20%. Thus, the number of inactive traders fluctuates around 80%. Hence, there are more fundamentalist traders left compared to trend-chasing traders indicating that this low tax rate might have the potential to stabilize financial markets. However, 80% of traders are not trading which indicates a loss of liquidity. An absence of autocorrelation in raw as well as in absolute returns can be inferred for the autocorrelation diagrams. Thus, volatility clusters are absent under taxation, a result which can also be found in Demary (2010). This result

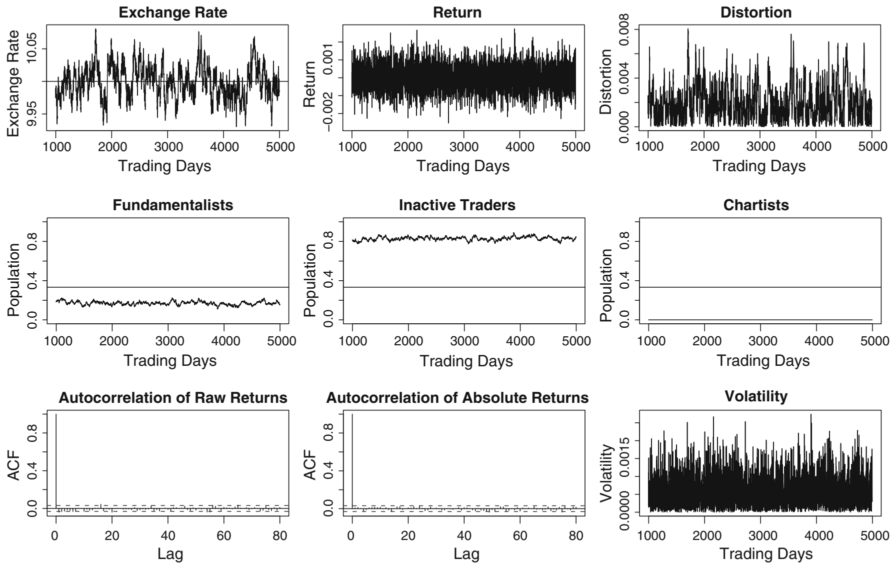

Fig. 2 Simulation of a stabilizing tax regime: 0.1% tax. *Notes* The output of a typical simulation run of a stabilizing tax regime. The underlying parameter values are those given in Table 1. Fundamental equilibrium values from the baseline case are given by the *horizontal lines* located at $\overline{s^F} = 10$ and $\overline{w^F} = \overline{w^C} = \overline{w^I} = 1/3$

is caused by the decline in the number of chartist traders, who account for a large fraction of the variation of returns through the SSV mechanism. Moreover, bubbles are less persistent compared to the baseline simulation. This outcome is due to the fact that there are no chartist traders left in the market. Furthermore, returns look like white noise, while distortions seem to be unsystematic. The model outcome indicates that the tax rate 0.1% lies within a stabilizing tax regime.

Destabilizing Tax Regime Fig. 3 shows a simulation run under a tax rate of 1%. Under this tax rate chartists as well as fundamentalists abstain from trading. Since fundamentalists are absent, there is no driving force that connects the exchange rate to its fundamental value. As a result, the time series of distortions is highly persistent and seems to follow a random walk. Thus, the exchange rate seems to return to its fundamental value only with a small probablity. Moreover, volatility is rising in time, a phenomenon which is a characteristic of a random walk. The results indicate that the tax rate of 1% lies within a destabilizing tax regime. The results from Figs. 2 and 3 are in line with the u-shaped volatilty and misalignment response curves found in the models of Westerhoff (2003a, 2008) and Demary (2010). In the following lines we will get more insights into this point.

5.2 Comparison of different tax regimes

Figure 4 contains a comparison of different tax regimes. The tax rate ranges from 0 (baseline case) to 1% (destabilizing tax regime) and is varied in 0.05% point steps.

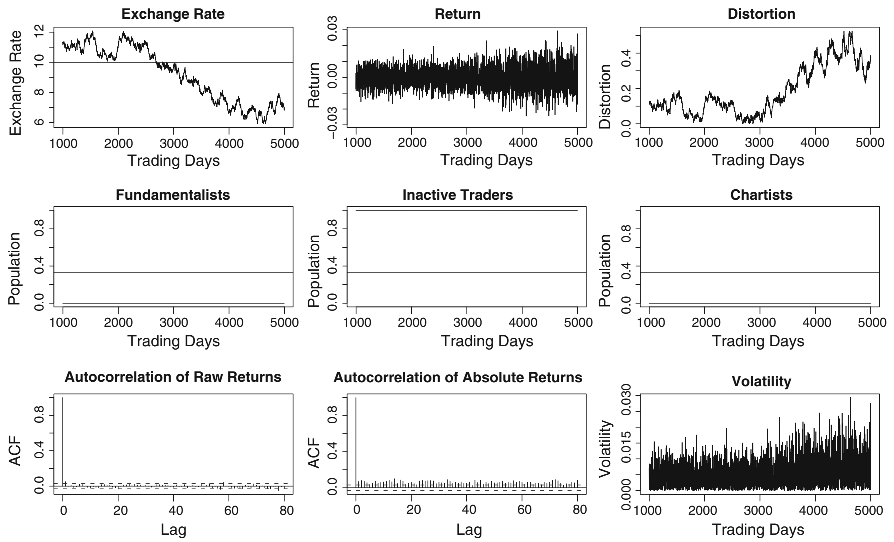

Fig. 3 Simulation of a destabilizing tax regime: 1% tax. *Notes* The output of a typical simulation run of a destabilizing tax regime. The underlying parameter values are those given in Table 1. Fundamental equilibrium values from the baseline case are given by the *horizontal lines* located at $\overline{s^F} = 10$ and $\overline{w^F} = \overline{w^C} = \overline{w^I} = 1/3$

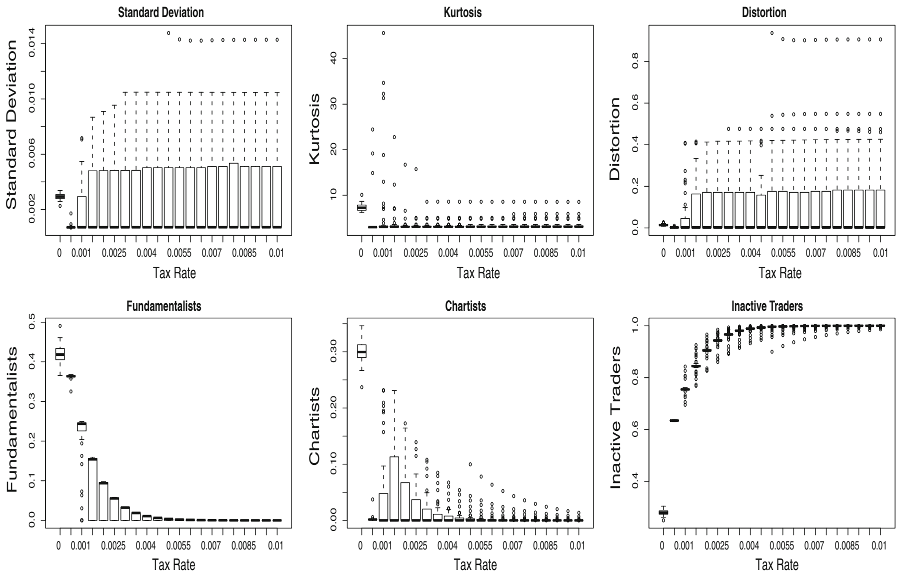

Fig. 4 Comparison of different tax regimes. *Notes* All *boxplots* are based on 6,000 artifical trading days and 50 simulation runs. The *middle line* of the box plots represent the median over 50 simulation runs, while the *ends of the boxes* represent the first and third quartiles. The *whiskers* indicate the most extreme point that is with a factor of 1.5 of the hinge. Any points beyond the whiskers are outliers. Note, that simulations for different tax rates are based on the same seed of random variables. The underlying parameter values are those given in Table 1

All simulations for different tax rates are based on the same seed of random variables. The figure shows volatility, distortion and the kurtosis, as well as the population fractions of chartists, fundamentalists and inactive traders as a function of the transaction tax rate. Remind, that 100% inactive traders indicate that there are no chartists and fundamentalists left in the market, while a constant fraction of noise traders is still trading.

From these figures can be inferred, that the number of chartists and fundamentalists are declining on average in the tax rate. Moreover, all chartists and fundamentalists are inactive on average for tax rates above 0.5%. Furthermore, the variation in these population fractions is increasing in the tax rate. This can be inferred from the larger boxes for larger values of the transaction tax rates. Moreover, there is a larger number of outliers for higher tax rates as well. However, the number of outliers for the number of chartists is larger compared to the outliers in the number of fundamentalists. These results indicate several speculative attacks of chartists.

The volatility of the exchange rate returns is decreasing on average in the tax rate. However, the variation in this statistic is increasing in the tax rate as well. This can be inferred from the larger boxes. Note that the whisker of the baseline case lies within the boxes for higher tax rates. Thus, there is a certain probability that taxation will increase the volatility of exchange rate returns as well. This is especially the case for the simulations in which the number of fundamentalists is near zero, which limits the reversion of the exchange rate towards its fundamental values. From the variation in the results of these policy experiments we can conclude that taxation might also lead to higher volatility with a certain probability.

The kurtosis statistic is decreasing in the tax rate on average. There are small boxes indicating that there is a small process error due to different seeds of random variables. Hence, taxing financial markets lead to a smaller number of large returns, that means to less crashes. However, there is as well a significant number of outliers. Thus, there are also simulation runs in which taxing financial markets lead to a higher frequency of crashes.

A similar picture can be found for the average distortion or excess volatility. Distortions are decreasing in the tax rate on average but the variation in this number is as well increasing in the tax rate. This can be inferred from the larger boxes for higher tax rates. Moreover, there is a significant number of large outliers. These results indicate that distortion might be declining on average. However, the large number of simulation runs in which it is increasing indicates that the stabilizing effect is not for sure and that there are significant cases where taxation has destabilizing effects. This is especially the case for the simulation runs, where the number of fundamentalists is near zero, while there is a larger number of chartist traders left. In these cases the reversion of the exchange rate towards its fundamental value is limited.

From these results we conclude that small taxes have the ability to stabilize the financial market, while higher tax rates have not. The stabilizing tax regime is departed from the destabilizing one by a tax rate of 0.1%. For tax rates below this threshold value the number of fundamentalists is higher compared to the number of chartists, while volatility and distortions are declinig in the tax rate. The reason for the destabilizing nature of higher tax rates is due to the fact, that these tax regimes are characterized by a higher uncertainty around the average behavior of volatility and distortions over

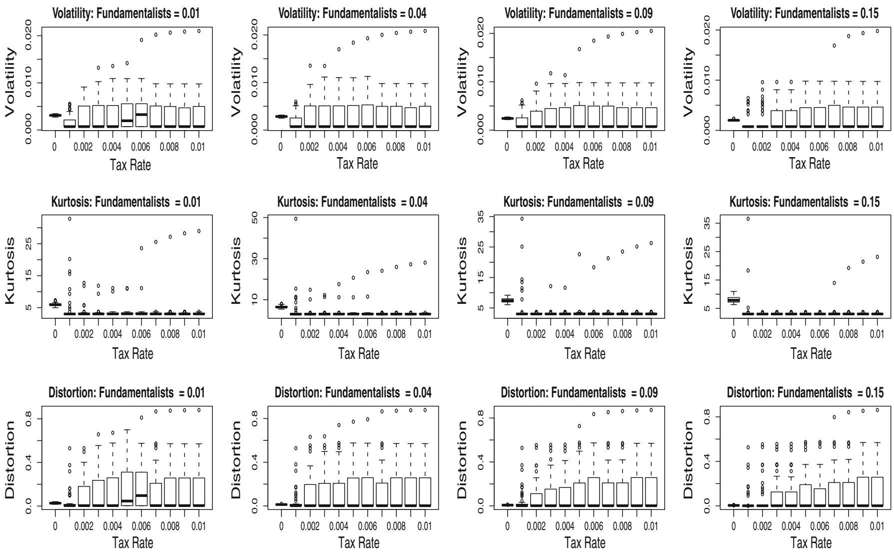

Fig. 5 Comparisons of different tax regimes for different degrees of fundamentalists' aggressiveness κ_F. *Notes* See Fig. 4

several simulation runs as indicated by the larger boxes. The uncertainty around these numbers is due to the larger outliers in the number of chartists for higher tax rates. In these cases, their number is higher compared to the number of fundamentalists, what explains the destabilization of the market. It seems that chartistm might be more profitable compared to fundamentalism under higher transaction cost at least for some cases. Comparable results can also be found in Westerhoff (2003a, 2008) and Demary (2010). The variation in our result might be due to the nonlinearity of the model and its sensitivity to different seeds of random variables.

5.3 Aggressiveness of fundamentalists

Figure 5 contains a comparison of different tax regimes for different degrees of the aggressiveness of fundamentalists. Results for volatility, kurtosis and distortions are given in boxplots. These boxplots contain averages over 6,000 artificial trading day plotted for 50 independent simulation runs. In contrast to Fig. 4 we provide plots for different degrees of aggressiveness with which fundamentalists trade. More precicely, we differentiate between the cases $\kappa_F \in \{0.01, 0.04, 0.09, 0.15\}$, while the tax rate is varied from 0 to 1% in 0.1% point steps. Note, that $\tau = 0.01$ means that the tax rate is 1%.

We figure out the u-shaped volatility response on average for $\kappa^F = 0.01$, the case in which fundamentalists act less aggressive compared to the baseline case. Moreover, there is large uncertainty around this median for larger tax rates, which is indicated by the wider boxes and whiskers. The kurtosis seems to decline in the tax rate on average, however, there are large outliers especially for larger tax rates. A u-shaped response

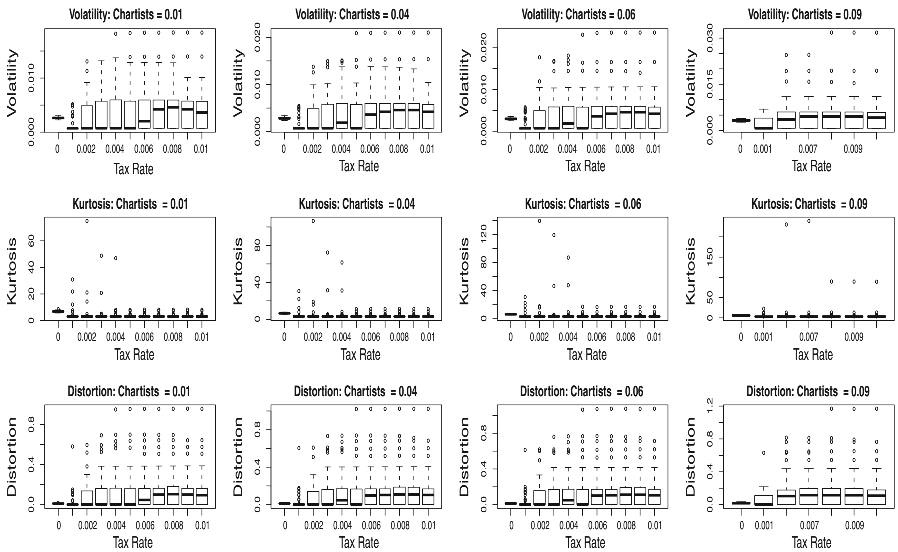

Fig. 6 Comparison of different tax regimes for different degrees of chartists' aggressiveness κ_C. *Notes* See Fig. 4

of distortions to higher tax rates can be found as well. However, there are larger boxes and whiskers for higher tax rates indicating more variation in this measure over the 50 simulation runs.

For larger values of κ^F we find that volatility is declining especially for higher tax rates. However, fluctuations in this statistics are not decreasing in the fundamentalists aggressiveness. For $\kappa^F = 0.15$ we find smaller boxes for lower tax rates, but a larger number of outliers. Distortions are declining on average in the tax rate when fundamentalists act more aggressively. Moreover, we find smaller boxes and whiskers at least for small tax rates. Furthermore, we find a reduction in the number of outliers for this measure, when fundamentalists act more aggressively.

Summing up, these results are in line with the conventional view, that more aggressive fundamentalists act as a stabilizing force. This can be inferred from the volatility and misalignment response curves which become flatter the more aggressively fundamentalists trade. A comparable result can be found in the model used in Demary (2010). We conclude, that taxation is more effective, when fundamentalists trade more aggressively.

5.4 Aggressiveness of chartists

Figure 6 contains a comparison of different tax regimes for different degrees of chartists' aggressiveness. A higher value of this parameter indicates that chartists place larger orders for a given trend segment and, hence, trade more aggressively. We consider the cases $\kappa^C \in \{0.01, 0.04, 0.06, 0.09\}$.

The u-shaped volatility response to taxation becomes flatter for small tax rates the less aggressively chartists trade. The smallest box can be found for a tax rate of 0.1%,

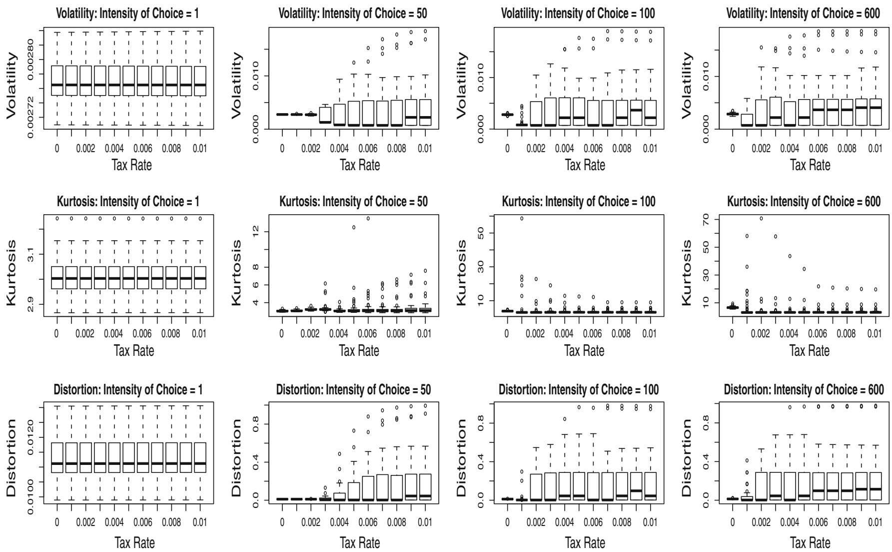

Fig. 7 Comparison of different tax regimes and different intensity-of-choice measures γ. *Notes* See Fig. 4

while boxes increase in size for tax rates above this value. Larger boxes indicate a larger variation through different simulation runs. For increasing tax rates we figure out that whiskers become more narrow, while outliers of the volatiliy increase in magnitude, when chartists become more aggressive. The higher frequency of outliers might be caused by more frequent speculative attacks when chartist act more aggressively.

For $\kappa^C = 0.09$ we find that chartists destabilize since we find the highest number of outliers of volatility for this value of the trend-extrapolation parameter. Large outliers of the kurtosis measure increase especially for higher transaction tax rates, when trend-chasing agents act more aggressively. The large outliers of this statistic which indicates large absolute returns in a sample indicates that there are infrequent speculative attacks caused by chartists' aggressiveness.

We figure out a *u*-shaped distortion response curve for rising tax rates as well. The picture which emerges from the box plot is more or less robust to different values of the chartists' aggressiveness. For the case $\kappa^C = 0.09$ we find more outliers and more variation as indicated by a larger box for the case of a 0.1% transaction tax.

Summing up, the results indicate that a higher aggressiveness of chartists leads to a destabilization and a smaller effectiveness of transaction taxes in financial markets. The smaller effectiveness can be infered from the volatiliy response curve which becomes flatter on average the less aggressively chartists act. Similar findings can be found in the sensitivity analysis in Demary (2010).

5.5 Intensity of choice

Figure 7 contains a comparison of different tax regimes for different values of the agent's intensity-of-choice parameter. A higher value of this parameter indicates that agents switch more often between trading strategies for maximizing profits.

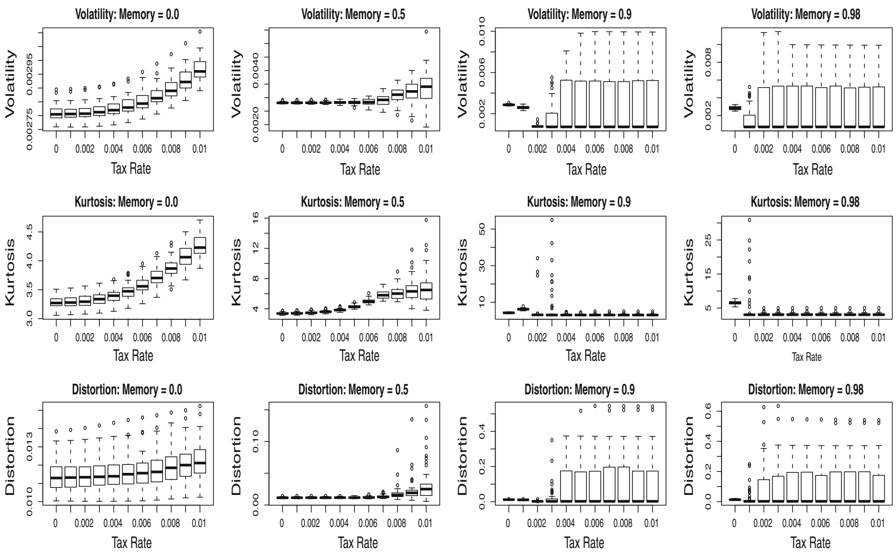

Fig. 8 Comparison of different tax regimes for different memory parameters θ. *Notes* See Fig. 4

The case $\gamma = 1$ is the case where agents react more sluggish to changes in the performance measures. As a result, flat volatility, kurtosis, and distortion response curves to taxation emerge. Moreover, the kurtosis measure corresponds to the one of the normal distribution.

For the case $\gamma = 50$ and for higher values of this parameter a u-shaped volatility response curve emerges. Volatility reductions can be found for tax rates between 0.3 and 0.8 but not for tax rates below 0.3%. For rising tax rates boxes and whiskers increase indicating more variation for different simulation runs. For $\gamma = 100$ we find that the tax rates 0.1 and 0.2% become stabilizing, since they decrease volatility now. However, we figure out that the tax rate 0.3% increases volatility when we enlarge γ to the value 600.

As already mentioned, we find that the kurtosis of the exchange rate return distribution equals the one of the normal distribution on average for $\gamma = 1$, while the kurtosis increases when the parameter γ takes higher values. Moreover, we figure out more outliers for this statistic. Thus, higher values of the intensity-of-choice measure might cause large trends and crashes in returns. This finding makes sense since more agents switch to the most profitable trading rule under a higher value of γ. From this more aggressive trading behavior more turbulent and more quite phases emerge, which summarizes in a more leptukurtic exchange rate return distribution. Moreover, we find larger variations in the distortion measure and more outliers, as indicated by the larger boxes and whiskers.

We conclude, that a more aggressive switching of agents between different trading strategies destabilize the financial market and lowers the effectiveness of higher transaction taxes, which is indicated by the shifts in the volatility response curve.

5.6 Profit discounting

Figure 8 contains a comparison of different tax regimes for different values of the agents' memory parameter $\theta \in \{0, 0.5, 0.9, 0.98\}$. A higher value of this parameter θ indicates that past profits are taken into account for the current strategy selection, while a lower value of θ indicates that agents orientate only on recent profits for determining their investment strategy. When $\theta = 0$, then agents consider the last periods profit only, hence, the agent will react apruptly to changes in the performance measures. From Fig. 8 can be inferred, that volatility, kurtosis as well as distortions are rising in the transaction tax rate for the case $\theta = 0$. Thus, taxation leads to a destabilization of the market, when agents are very aggressive and only consider their short-term profits for strategy selection.

When the memory parameter takes the value $\theta = 0.5$ the profits of the last days are as well relevant for strategy selection. In this case, volatility, kurtosis and distortions are as well increasing in the tax rate, while also the dispersion of these statistics is increasing in the tax rate as indicated by the larger boxes and whiskers. Hence, there is increasing variability over several simulation runs. For tax rates near 1% there are large outliers of distortions and kurtosis indicating erratic fluctuations for some simulation runs.

For the case of a memory parameter $\theta = 0.9$ traders' performance measure takes even the profits some weeks ago into account. In this case volatility is declining for tax rates below 0.3%, while this decline is not significant for higher tax rates which can be inferred from the larger boxes which indicate a larger variability of this statistic. From the larger whiskers can be inferred, that there are a lot of simulation runs in which volatility is increasing for higher transaction tax rates. A similar result can be found for the kurtosis measure. Here, the number of outliers is increasing for tax rates around 0.3% indicating that this regime can be destabilizing. The variation in the average distortions are increasing in the tax rate as well as indicated by the larger boxes and whiskers. As a result, higher tax rates lead to larger deviations from the fundamental values for a large part of our simulation runs.

We find, that for a large part of our simulations volatility seems to increase in the tax rate. A simular result can be found for distortions, although a large number of outliers can even be found for a 0.1% tax. The results indicate that agents' discounting of past profits plays a role for the stabilizing impact of transaction taxes. Although taxation works on average, when agents take a large part of past profits into account, we find in a significant part of our simulations that taxation can also have destabilizing effects.

Figure 10 contains comparable results to Fig. 9, but is based on a simulation of model 4 instead. As can be seen, results only change slightly, which indicates that our results apply to different parameterizations of the model.

We conclude from the shape of the volatility response curve that taxation becomes more effective the longer the memory of the traders is.

5.7 Risk aversion

Figure 9 contains a comparison of different tax regimes for different degrees of risk aversion. A larger value of this parameter indicates that agents are more careful and

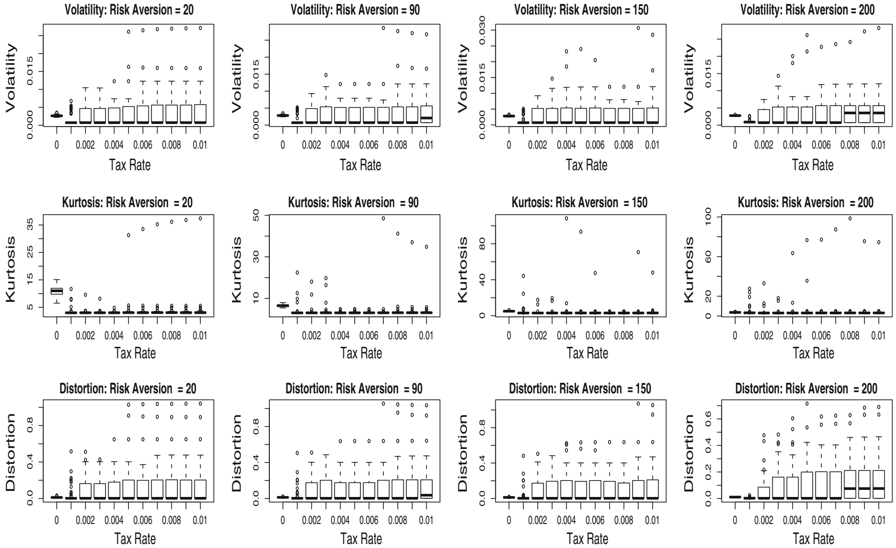

Fig. 9 Comparison of different tax regimes under different degrees of risk aversion μ (Model 1). *Notes* See Fig. 4

place smaller orders. Hence, agents that are less risk averse tend to be more aggressive, since they tend to trade larger orders. We analyze the cases $\mu \in \{20, 90, 150, 200\}$. For $\mu = 200$ we find the u-shaped volatility response curve, which diminishes for lower values of this parameter. In more detail, we find that volatility is smaller on average for tax rates above 0.7%, when agents are less risk averse. Hence, higher transaction taxes seems to be more effective, when agents are less risk averse. When traders have a higher degree of risk aversion, we find larger outliers in the kurtosis measure. Moreover, we find less outliers for smaller taxes, when traders are less risk averse. We find a u-shaped distortions response curve on average, when traders are risk averse ($\mu = 200$), while distortions decrease in magnitude for higher tax rates, when traders are less risk averse.

Figure 10 contains comparable results but under the parameterization of model 4, which leads to higher volatility. Since volatility has direct effects on the decisions of risk averse agents, policy implications might change under a calibration that produces higher volatility. From Fig. 10 can be infered that under this parameterization higher transaction taxes lead to smaller distortions the less risk averse traders are. This result is line line with the implications from Fig. 9. Again we find, that transaction taxes are more effective the less risk averse traders are.

6 Conclusion and outlook

Recent agent-based financial market models came to the result that taxing financial transactions does not per se increase financial stability and that the response of volatility and distortions to rising tax rates seem to be u-shaped. Moreover, greed and

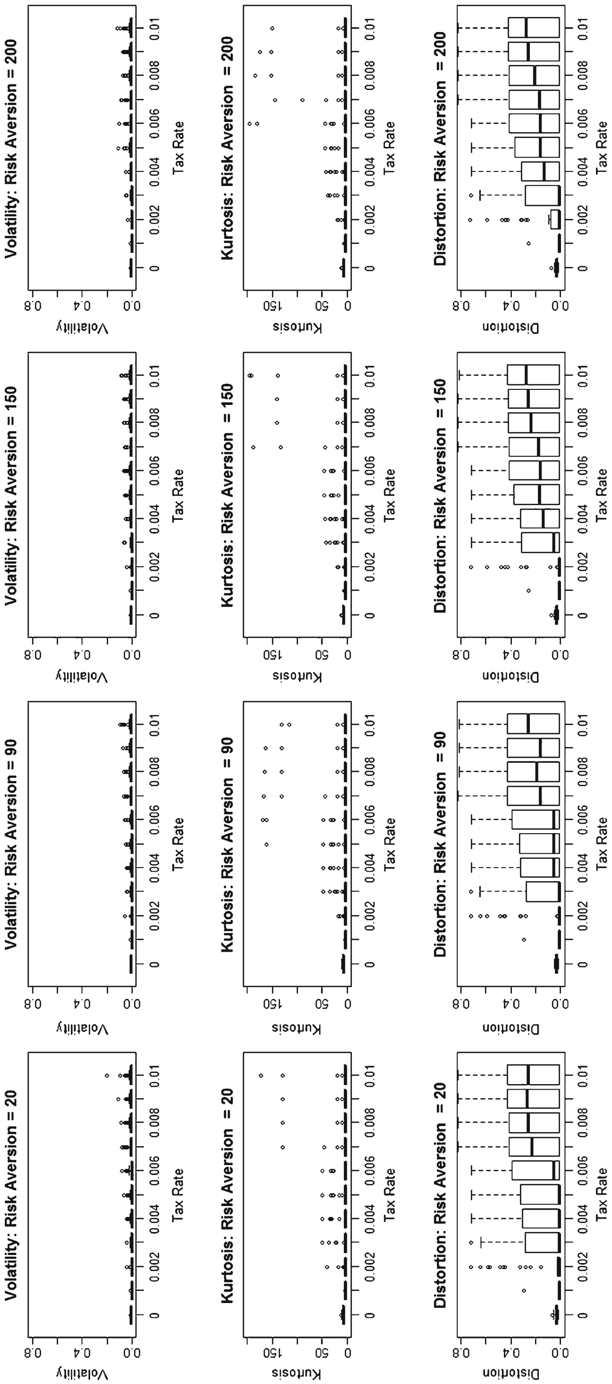

Fig. 10 Comparison of different tax regimes under different degrees of risk aversion μ (Model 2). *Notes* See Fig. 4

the risk appetite of traders are often blamed for financial instability and there is no evidence how behavioral patterns affect the effectiveness of regulations in financial markets. We aim to fill this gap in the literature by analyzing how different degrees of risk aversion and aggressiveness of traders affect the working of transaction taxes within an agent-based framework.

We introduce financial market taxes into the model proposed by DeGrauwe and Grimaldi (2006), which explicitly assumes risk averse traders. Moreover, we expand the original model by structural stochastic volatility as proposed by Franke and Westerhoff (2009), Westerhoff (2008) and Westerhoff and Dieci (2006), since it is an important generator of volatility clusters (Franke and Westerhoff 2009).

Within the model the following results emerged: (i) The tax rate 0.1% seems to demarcate the stabilizing tax regime from the destabilizing tax regime. (ii) The shapes of the volatility-response-curve and the distortion-response-curve depend on the agents risk aversion. Both are u-shaped when agents are highly risk averse, while the curves become flatter the less risk averse agents are. From these results we can conclude that transaction taxes are more effective the less risk averse traders are. (iii) More aggressive fundamental trading makes financial market taxes more effective, which is indicated by a flatter volatility response curve. (iv) More aggressive chartists makes small taxes less effective. This results can be inferred from the flatter volatility response curve for lower degrees of chartists' aggressiveness. (v) The more agents switch to the most profitable trading rule, the steeper the response curves are for higher tax rates. We conclude that transaction taxes are less effective the higher this parameter is. (vi) Longer memory in the performance measures makes transaction taxes more effective as indicated by a flatter response curves for lower values of this parameter.

Further research should concentrate on behavioral heterogeneity in risk aversion. We find that transaction taxes are more effective the less risk-averse traders are. This finding might depend on a configuration with more fundamentalists compared to chartists and might not be valid under a configuration with less fundamentalists than chartists. We should expect that markets with less risk-averse fundamentalists and more risk-averse chartists are more stabile compared to markets with more risk-averse fundamentalists and less risk-averse chartists. Moreover, transaction taxes should be more effective in markets with more aggressive fundamentalists. The reason lies in the fact that less risk-averse fundamentalists place larger orders against a mispricing compared to a less risk-averse ones, while more risk-averse chartists places smaller orders to a given trend segment compared to a less risk-averse ones. Hence, introducing heterogeneity in risk aversion might give additional insights to the working of financial markets and the effectiveness of regulations.

This heterogeneity in risk aversion of chartists and fundamentalists might have important implications for the implementation of regulations. As highlighted in the introduction, Menkhoff and Schmidt (2005) finds that buy-&-hold traders behave fundamentally oriented and risk averse, while momentum traders are less risk averse and follow aggressively the trend. Hence, policy measures for ensuring financial stability should delimit the risk-exposure of chartists, while they should allow fundamentalists to aggressively arbitrage away mispricings. Therefore, additional regulations should concentrate on the traders' responsibilities for their risk-exposure.

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