Transaction Taxes and Traders with Heterogeneous Investment Horizons in an Agent-Based Financial Market Model[1]

Markus Demary[2]
Doctoral Program "Quantitative Economics", University of Kiel
Cologne Institute for Economic Research[3]

December 28, 2009

Abstract: This agent-based financial market model is a generalization of the model of Westerhoff (2008a) by traders who are allowed to have different investment horizons as introduced by Demary (2008). Our research goals are, first, to study what consequences the introduction of heterogeneous investment horizons has for agent-based financial market models and second, how effective transaction taxes are in stabilizing financial markets. Numerical simulations reveal that under sufficiently small tax rates traders abstain from short-term trading in favour of longer investment horizons. This change in behavior leads to less volatility and less mispricings. When the tax rate exceeds a certain threshold, however, mispricings increase as also found in Westerhoff (2003a, 2008a). This emergent property is due to the fact that taxation reduces short-term fluctuations and causes longer lasting trends in the exchange rate. As a result, the longer term fundamentalist trading rules becomes unpopular in favor of the longer term trend-chasing rule.

Key words: *Agent-Based Financial Market Models, Financial Market Stability, Regulation of Financial Markets, Technical and Fundamental Analysis, Transaction Taxes*

JEL Classification: *C15, D84, G01, G15, G18*

---

[1]**Acknowledgements:** I would like to thank Thomas Lux, Frank Westerhoff as well as two anonymous referees for many helpful comments and suggestions.

[2]**Author's contact details:** Cologne Institue for Economic Research, Konrad-Adenauer-Ufer 21, 50668 Köln, Germany. Email: demary@iwkoeln.de, Phone: 49-221-4981-744.

[3]The views expressed in this paper are those of the author and do not necessarily represent those of the Cologne Institute for Economic Research.

1 Introduction

Asset prices are excessively volatile and risky (LeRoy and Porter 1981, Shiller 1981) due to speculative bubbles and crashes. Because large asset price crashes lead to severe recessions, research on the occurance of asset price bubbles and their avoidance through financial market regulations is a highly relevant topic for economic scientists, economists in firms and institutions as well as for economic policy makers. Because empirical case studies of financial market regulations lack of sufficiently rich datasets, agent-based financial market simulations are promising tools for analysing the effectiveness of policy measures[4].

Famous proposals of financial market regulations go back to Keynes (1936) and Tobin (1978) who proposed to introduce taxes on financial markets in order to reduce speculative trading. Both assume that short term traders have a destabilizing impact on prices, while long term traders' trading behavior is stabilizing. Both suggest that the introduction of a transaction tax will harm short-term speculators more compared to longer term investors. The rationale behind this proposal is that a round trip of borrowing money in one country, investing it in another country and consuming the profit in the home country will lead to higher transaction costs the more frequent transactions takes place. Some empirical papers, however, find that the introduction of transaction taxes may be destabilizing[5]. Westerhoff (2008a) notes that these empirical studies are not without problems. Umlauf (1993), for example, analyzes Swenden's introduction of a 2 percent securities transaction tax, which is following Westerhoff (2008a) a quite high tax rate. Sweden abolished the financial market tax because it did not lead to the expected success. Insights to the failure of this real world policy experiment can be given by referring to the heterogeneous agents model proposed by Westerhoff (2003a). This model predicts that small transaction taxes are stabilizing, while higher transaction taxes are destabilizing. The reason is that different tax rates have a different impact on the composition of stabilizing and destabilizing trading rules. A small tax rate makes destabilizing trading rules unprofitable, while a higher tax rate also makes stabilizing trading rules unprofitable.

Inspired by this result, Westerhoff (2008a) suggests to analyze the effectiveness of small transaction taxes on financial markets by means of agent-based financial market models. Lux (2009b) highlights that agent-based models are preferable tools for doing policy experiments which are close to reality. Westerhoff (2008a) surveys the following advantages of agent-based policy analysis: *(i)* The researcher is able to generate a huge amount of data, *(ii)* is able to measure all variables precisely, *(iii)* is able to control for exogenous shocks and special events and simulate them by varying a policy parameter under otherwise same conditions. In this way the researcher is able to analyze how a certain policy performs under these special events. *(iv)* Finally, the researcher is able to measure the behavior of artificial agents during the simulations.

[4]See Westerhoff (2008a) for an survey of the advantages of agent-based financial market models and applications of financial market regulations like transaction taxes, trading halts and central bank interventions.

[5]See for example Umlauf (1993), Jones (1997), Aliber (2003), Hau (2006).

Up to now, there is a growing body of articles which employ agent-based models for the analysis of the effectiveness of currency transaction taxes[6]. We already referred to Westerhoff (2003a) who finds that small currency transaction taxes lower exchange rate volatility, while higher tax rates lead to an increase in volatility. Westerhoff and Dieci (2006) propose an agent-based model in which traders are allowed to trade in two different financial markets. The model predicts that when a policy maker levies a transaction tax only onto one market, the volatility in this market will decline, while the volatility in the second market will increase. The reason is that trend-chasing trading rules are more profitable in the untaxed market. The second result of their article is, that levying the tax on both markets, will lead to a decline in the volatilty in both markets. Demary (2008) introduces an artificial foreign exchange market with chartists and fundamentalists who are allowed to choose between being a day trader and being a longer term trader. Levying a transaction tax onto this artificial foreign exchange market leads to an increase in the kurtosis of the return distribution, which means a higher probability of large positive and negative returns. This increased probability of extreme returns emerges from the changed composition of short-term and longer term traders. Under taxation short-term trading becomes unprofitable relative to longer term trading. Short-term traders who normally trade small orders every day now decide to trade larger orders every 30 days. This increase in larger orders leads to an increase in the kurtosis of the return distribution. Pelizzari and Westerhoff (2007) show that transaction taxes are only effective under certain market structures, while they will not work under some specific market structures. Summing up, all these studies reveal important insights for economic policy makers into the effects of currency transaction taxes on financial markets.

In this paper we enlarge the artifical financial market of Westerhoff (2008a) by the trader types with different investment horizons of Demary (2008)[7]. Our first objective is to study the implications of longer term investment horizons for exchange rate dynamics in agent-based models, the second one is to use this artificial laboratory for analyzing the effectiveness of currency transaction taxes. The analysis of these two objectives can be combined to analyzing the joint hypothesis that *transaction taxes stabilize financial markets by crowding out short term speculators in favor of longer term investors.* In line with the literature we are interested in how this regulatory policy changes emergent properties that arise from the changed interaction of traders, like bubbles and crashes, excess volatility, volatility clustering and the fat-tailness of the return distribution.

Within our model the following results emerge. Numerical simulations of our artificial financial market reveal that emergent properties and stylized facts still remain when longer term traders are introduced. The economic policy analysis reveals

[6]Other policy applications of agent-based models are Westerhoff (2001), Wieland and Westerhoff (2005), Westerhoff and Wieland (2004), Westerhoff (2008a) who analyze the effectiveness of central bank interventions. Westerhoff (2003b), Westerhoff (2006) and Westerhoff (2008a) analyze the effectiveness of trading halts for stabilizing financial markets. Weidlich (2008) introduce an agent-based model for analyzing electricity market regulation, while Haber (2008) uses an agent-based model for monetary and fiscal policy analysis.

[7]Note, that under the restriction that all traders have a short-term investment horizon, our model collapses to Westerhoff's model.

that small transaction taxes make short-term trading unprofitable. Therefore, the number of short-term fundamentalists and short-term chartists decreases to zero. Moreover, volatility and distortions decrease under small transaction taxes. The reason for this result lies in the fact that under small transaction taxes the market is populated by a larger fraction longer term fundamentalist traders in relation to longer term chartist traders. However, when tax rates are too high, misalignments increase as also found in Westerhoff (2003a, 2008a). The reason for this u-shaped response of misaligments to increasing tax rates is caused by the changed composition of used trading rules. When tax rates are too high the longer term fundamentalist trading rule becomes unpopular, while the number of traders, who favor the longer term chartist trading rule increases. The reason lies in the fact that short-term traders abstain from trading under transaction taxes. The diminishing short-term fluctuations lead to longer swings in the exchange rate, which makes longer term chartist trading rules more profitable. In contrast to Keynes (1936) and Tobin (1978) taxing financial markets is not *per se* stabilizing by making short-term trading unprofitable in favor of longer term trading. Our model shows that this result is not independent of the composition of the used trading rules in the financial market and not independent of the tax rate.

The remainder of this paper is organized as follows. The next section introduces the artifical foreign exchange market, while section three will present an analysis of the model's steady state. Section four tackles the validation of this model, while section five discusses the simulation results. Section six ends this paper with conclusions and outlook.

2 Transaction Taxes in an Agent-Based Financial Market Model

In this section we introduce the agent-based financial market which is a generalization of the model proposed by Westerhoff (2008a), which can represent either a foreign exchange market, a stock market or a commodity market (Westerhoff 2008). We interpret it as a foreign exchange market and calibrate it to exchange rate data, here. Following Demary (2008) we introduce longer term traders into this model. If all traders have a daily investment horizon, then our model collapses to Westerhoff's. Influential contributions to agent-based financial market models[8] are surveyed in Westerhoff (2008b), Hommes (2006), LeBaron (2006) and Lux (2009a, 2009b). All models have in common that agents choose from a finite set of behavioral rules. Commonly, these are a fundamental trading rule, which reacts to deviations of the asset price from its fundamental value, and a chartist trading rule, which reacts on trends in the asset price. The former one has a centripetal effect on the asset price dynamics, while the later one has a centrifugal effect (Lux 2009a). These heterogenous agents are either assumed to consist of a finite population (Kirman 1991) or of a continuum of agents (Brock and Hommes 1998). Moreover, models may differ

[8] Important and influencial contributions are Day and Huang (1990), Kirman (1991), Chiarella (1992), Chiarella and He (2002), DeGrauwe and Grimaldi (2006), Lux (1995), Lux and Marchesi (1999, 2000), Brock and Hommes (1998), LeBaron (1999) and Farmer and Joshi (2002).

in the assumed process for the evolution of used heterogeneous trading rules. While in Brock and Hommes (1998) and DeGrauwe and Grimaldi (2006) the popularity of trading rules is governed by the past success of these rules, in Kirman (1991) and Lux and Marchesi (1999, 2000) the evolution of trading rules is governed by social interactions. LeBaron (1999) uses genetic algorithms as evolutionary processes. Macroscopic properties of the asset price like bubbles and crashes, excess volatility, excess kurtosis of the return distribution and volatility clustering emerge from the interaction of agents. Note that these properties cannot simply be deduced by aggregating agents (Westerhoff 2008a) but emerge independent of the microscopic properties (Lux 2009a). An example for an emergent property is the occurance and burst of a speculative bubble. When the majority of agents relies on chartist rules a speculative bubble can emerge, when this bubble makes fundamental rules more popular and agents switch to this trading strategy, this change in behavior results in a crash back to the fundamental value. Summing up, these models are quite successful in replicating stylized facts of daily financial market data (Lux 2009a).

Similar to Demary (2008) we want to analyze in detail the following proposition - which is often heard from the proponents of transaction taxes and the public media especially in times of financial instability - within our artificial financial market: *transaction taxes stabilize asset prices by crowding out short-term speculators in favor of longer term investors.* In order to analyze this proposition we have to consider the following requirements and assumptions:

(i) *we need a model in which we are able to distinguish between short-term traders and longer term investors,*

(ii) *the number of short-term traders and longer term traders should not be fixed but traders should be allowed to change groups or leave the market, and*

(iii) *the model should be able to match empirical properties of financial market data in order perform policy experiments which are close to reality.*

For fulfilling requirements (*i*), (*ii*) and (*iii*) the most appealing framework is an agent-based model of a financial market. This artificial foreign exchange market should consist of the following building blocks

(i) *a fundamental exchange rate* s_t^f*, which is purely determined by exogenous factors (e.g. monetary aggregates, current accounts, business cycle conditions, ...)*

(ii) *traders who choose from a finite set of possible trading rules: a short-term fundamentalist rule, a short-term chartist rule, a longer term fundamentalist rule, a longer term chartist rule, or being inactive,*

(iii) *an evolutionary mechanism for determining the popularity of a certain trading rule according its past performance,*

(iv) *a market maker who adjusts the exchange rate in response to excess demand,*

(v) *a policy maker who determines the value of the currency transaction tax rate.*

We will elaborate this building blocks in more detail.

2.1 Traders' Demand for Foreign Currency

Westerhoff (2008a) models the agents' demand in line with the literature on heterogeneous agents models of financial markets (Brock and Hommes 1998, Day and Huang 1990, Lux 1995, Lux and Marchesi 2000, DeGrauwe and Grimaldi 2006), but adds random disturbances to the agents' demands in order to account for the empirical variety of trading rules. Thus, short-term chartists' (SC) demand is given by

$$d_t^{SC} = \kappa_C(s_t - s_{t-1}) + \varepsilon_t^C, \text{where } \varepsilon_t^C \sim \mathcal{N}(0, \sigma_C^2), \tag{1}$$

while short-term fundamentalists' (SF) demand is given by

$$d_t^{SF} = \kappa_F(s_t^f - s_t) + \varepsilon_t^F, \text{where } \varepsilon_t^F \sim \mathcal{N}(0, \sigma_F^2). \tag{2}$$

Chartists trade foreign currency because they expect the recent trend $(s_t - s_{t-1})$ to sustain in the next period. The parameter κ_C governs the strength of the trend extrapolation. Note, that s_t is the exchange rate in logarithmic notation, thus, $s_t - s_{t-1}$ is the percentage change in the exchange rate. Chartists expect to make profits by buying (selling) the exchange rate at s_t and selling (buying) it at the expected higher (lower) value s_{t+1}. Following Westerhoff (2008a), the random disturbance ε_t^C accounts for the variety of possible chartist trading rules. Fundamentalists buy (sell) foreign currency when the current exchange rate s_t is below (above) the fundamental one s_t^f. The reason is that this group expects the exchange rate to return to its fundamental value in the future, where κ_F is the assumed rate of misalignment-correction. Thus, fundamentalist traders expect profits by buying (selling) foreign currency at the exchange rate s_t and selling (buying) it at the higher (lower) one s_{t+1}, which they assume to be close to the fundamental value s_t^f. The fundamental value is assumed to be purely exogenous. Westerhoff (2008a) adds the random disturbance ε_t^F to this equation, which should represent a percention error or a deviation from the strict deterministic trading rule.

In addition to these two trading rules we assume, following Demary (2008), two longer-term trading rules for chartists and fundamentalists. The rationale behind this assumption is that traders assume a longer lasting trend in the exchange rate[9] or they expect a longer convergence period to the fundamental value. Longer-term chartists (LC) demand is given by

$$d_t^{LC} = \left[\frac{1 - (\kappa_C)^N}{1 - \kappa_C}\kappa_C\right](s_t - s_{t-1}). \tag{3}$$

More precise, it is the chartists' demand for an investment horizon of N days. For $N = 1$ this trading rule collapses to the conventional one period chartist rule. This trading rule can be derived as follows. When a longer term chartist trader observes the current trend segment $s_t - s_{t-1}$ he or she will expect a trend of $\kappa_C(s_t - s_{t-1})$ for the next period. For calculating the following exchange rate change, the trader uses this forecast and calculates $(\kappa_C)^2(s_t - s_{t-1})$ for the following period. Thus,

[9]See Engel and Hamilton (2000) for an empirical analysis of long swings in exchange rates.

the expected exchange rate change $s_{t+N} - s_t$ conditional on the chartists' rule is nothing else as the sum over all one period forecasts. By applying the rule for the finite geometric series equation (3) can be derived. Following Demary (2008) the longer-term fundamentalists' (LF) demand is given by

$$d_t^{LF} = \Big[1 - (1-\kappa_F)^N\Big](s_t^f - s_t). \tag{4}$$

This trading rule can be derived by the following consideration. When fundamentalist traders observes the misalignment $s_t^f - s_t$ he or she expects $\kappa_F{\cdot}100\%$ of this misaligment to be corrected by the next exchange rate change. Thus, he or she expects $(1-\kappa_F){\cdot}100\%$ of the misalignment to prevail, of which $\kappa_F(1-\kappa_F){\cdot}100\%$ will be corrected by the subsequent exchange rate change an so on. Thus, the expected exchange rate change $s_{t+N} - s_t$ conditional on the fundamentalist forecasting rule is nothing else as the sum over all one period forecasts. Again, by applying the formula for the finite geometric series equation (4) can be derived. Note, that for $N = 1$ this rule collapses to the conventional one period fundamentalist rule. Furthermore, note that we do not add random disturbances to the longer term trading rules. The reason is that we assume longer term trading rules to be more robust compared to one period rules.

2.2 Price Adjustment

Westerhoff (2008a) assumes following Farmer and Joshi (2002) a price impact function which can be interpreted as a stylized description of a risk-neutral market maker. Following Westerhoff (2008a), this market maker mediates transactions out of equilibrium and adjusts prices in response to excess demand. More precisely, the market maker will rise the exchange rate when excess demand for foreign currency is positive, while he will lower the exchange rate in response to negative market demand D_t

$$s_{t+1} = s_t + \beta D_t + \varepsilon_t, \text{where } \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2). \tag{5}$$

Market demand D_t is defined as the sum of orders of fundamentalist traders and chartist traders weighted by their pertinent population weights w_t^{SC}, w_t^{SF}, w_t^{LC} and w_t^{LF}

$$D_t = w_t^{SC} d_t^{SC} + w_t^{SF} d_t^{SF} + w_t^{LC} d_t^{LC} + w_t^{LF} d_t^{LF}. \tag{6}$$

Westerhoff (2008a) adds the random disturbance ε_t to the market maker's price adjustment rule, because it only represents a simple representation of real markets. From equations (5) and (6) can be inferred that the orders of the four trader groups as well as their population fractions determine exchange rate dynamics in a nonlinear way.

2.3 Evolution of Trading Rules

In the model of Westerhoff (2008a) traders have three alternatives. They can either be a fundamentalist trader or a chartist trader. The third possibility for traders is to stay inactive. In our version of this model traders have two additional alternatives. They can either be a longer term chartist or a longer term fundamentalist. Following Brock and Hommes (1998), DeGrauwe and Grimaldi (2006) and Westerhoff (2008a) the selection of one of these five alternatives depends on the strategies' past performances. The rationale behind this is an evolutionary mechanism in which more agents prefer to follow the trading rule which was most profitable in the past. Note, that this mechanism does not model herding behavior explicitly because there is no social interaction[10]. Inspired by Westerhoff (2008a) we assume the following fitness functions for short-term fundamentalist and short-term chartists

$$\begin{aligned} A_t^{SC} &= (\exp\{s_t\} - \exp\{s_{t-1}\})d_{t-2}^{SC} \\ &- \tau(\exp\{s_t\} + \exp\{s_{t-1}\})|d_{t-2}^{SC}| + \theta A_{t-1}^{SC} \end{aligned} \tag{7}$$

$$\begin{aligned} A_t^{SF} &= (\exp\{s_t\} - \exp\{s_{t-1}\})d_{t-2}^{SF} \\ &- \tau(\exp\{s_t\} + \exp\{s_{t-1}\})|d_{t-2}^{SF}| + \theta A_{t-1}^{SF}. \end{aligned} \tag{8}$$

The first term of the performance measures A_t^{SC} and A_t^{SF} is the return the agent got by investing in foreign currency by placing his or her order d_{t-2}^{SC} or d_{t-2}^{SF} to the market maker. Here, Westerhoff (2008a) assumes that traders submit orders in period $t-2$, which are executed at period $t-1$. If a pertinent trading rule is profitable or not thus depends on the realized price in period t. The second term is the transaction cost the trader has to pay when executing orders. If the trader buys (sells) foreign currency at the price s_{t-1} he or she has to pay a tax amount of $\tau \exp\{s_{t-1}\}|d_{t-2}|$ on this transaction, where τ is the transaction tax rate. The trader only realizes a profit if he or she sells (buys) the currency back at the price s_t. Again, a tax will be levied on this transaction with the tax amount $\tau \exp\{s_t\}|d_{t-2}|$. Thus, Westerhoff (2008a) assumes a round trip where the investors have to pay the transaction tax twice. The parameter θ is a memory parameter. Thus, the last term measures how quickly profits are discounted for strategy selection. If θ is high, then past profits generated by this trading rule will be considered in todays strategy selection, while for $\theta = 0$ past profits do not play any role for todays strategy selection. For $d = 1$ all past profits will play a role for todays selection. The fitness measures for the longer term trading strategies A_t^{LC} and A_t^{LF} are

$$\begin{aligned} A_t^{LC} &= (\exp\{s_t\} - \exp\{s_{t-N}\})d_{t-N-1}^{LC}/N \\ &- \tau(\exp\{s_t\} + \exp\{s_{t-N}\})|d_{t-N-1}^{LC}|/N + \theta A_{t-1}^{LC} \end{aligned} \tag{9}$$

$$\begin{aligned} A_t^{LF} &= (\exp\{s_t\} - \exp\{s_{t-N}\})d_{t-N-1}^{LF}/N \\ &- \tau(\exp\{s_t\} + \exp\{s_{t-N}\})|d_{t-N-1}^{LF}|/N + \theta A_{t-1}^{LF}. \end{aligned} \tag{10}$$

Following Demary (2008), we divide the profit generated by the multi-period investment through the investment horizon N. Thus, we measure the profit per day. This assumption is necessary in order to have a fair comparison between short-term trad-

[10] For herding models see Lux and Marchesi (1999, 2000) and Lux (2009a).

ing strategies and longer term strategies. Following Westerhoff (2008a) the profit of being inactive for one period is zero. Following Brock and Hommes (1998) and Westerhoff (2008a) the population fractions of agents are given by the discrete choice model proposed by Manski and McFadden (1981)

$$w_t^{SC} = \frac{\exp\{\gamma A_t^{SC}\}}{1+\exp\{\gamma A_t^{SC}\}+\exp\{\gamma A_t^{SF}\}+\exp\{\gamma A_t^{LC}\}+\exp\{\gamma A_t^{LF}\}} \tag{11}$$

$$w_t^{SF} = \frac{\exp\{\gamma A_t^{SF}\}}{1+\exp\{\gamma A_t^{SC}\}+\exp\{\gamma A_t^{SF}\}+\exp\{\gamma A_t^{LC}\}+\exp\{\gamma A_t^{LF}\}} \tag{12}$$

for short term traders,

$$w_t^{LC} = \frac{\exp\{\gamma A_t^{LC}\}}{1+\exp\{\gamma A_t^{SC}\}+\exp\{\gamma A_t^{SF}\}+\exp\{\gamma A_t^{LC}\}+\exp\{\gamma A_t^{LF}\}} \tag{13}$$

$$w_t^{LF} = \frac{\exp\{\gamma A_t^{LF}\}}{1+\exp\{\gamma A_t^{SC}\}+\exp\{\gamma A_t^{SF}\}+\exp\{\gamma A_t^{LC}\}+\exp\{\gamma A_t^{LF}\}} \tag{14}$$

for longer term traders, and finally

$$w_t^{I} = \frac{1}{1+\exp\{\gamma A_t^{SC}\}+\exp\{\gamma A_t^{SF}\}+exp\{\gamma A_t^{LC}\}+\exp\{\gamma A_t^{LF}\}} \tag{15}$$

for inactive traders, whose profits are zero by construction. Note that the higher the fitness of one particular strategy, the higher will be the percentage fraction of agents, who use it. The parameter $\gamma \geq 0$ controls how sensitive traders react to a change in the fitness measure of their trading rule. The higher γ the more agents switch to the strategy with the highest fitness. For $\gamma = 0$ all trading strategies will be selected with equal probability, while for $\gamma = \infty$ all agents select the strategy with the highest performance.

Note that for $N = 1$ (all traders have the same investment horizon) our model collapses to the model of Westerhoff (2008a).

3 (Non-)Fundamental Steady-States

In order to analyze the steady states of the model we have to set all shocks to zero and concentrate on the deterministic skeleton of the model. In order to be in steady state the restriction

$$(s_t, s_t^f, d_t^i, w_t^i, A_t^i) = (s_{t-1}, s_{t-1}^f, d_{t-1}^i, w_{t-1}^i, A_{t-1}^i) = (\overline{s}, \overline{s_t}, \overline{d^i}, \overline{w^i}, \overline{A^i}) \tag{16}$$

should hold ($i \in \{SF, LF, SC, LC, I\}$). Thus, all variables should be equal to their (fundamental) long run values and all dynamics should rest there. Under the restriction $s_t = s_{t-1} = \overline{s} = \overline{s^f}$ all fitness measures collaps to zero

$$\overline{A^{SC}} = \overline{A^{SF}} = \overline{A^{LC}} = \overline{A^{LF}} = 0 \tag{17}$$

leading to a uniform distribution of the popularity of all five trading rules

$$\overline{w^{SC}} = \overline{w^{SF}} = \overline{w^{LC}} = \overline{w^{LF}} = \overline{w^{I}} = 0.2. \tag{18}$$

Chartists' demand will be zero when the exchange rate remains constant

$$\overline{d^{SC}} = \overline{d^{LC}} = 0, \tag{19}$$

while the fundamentalists' demand will only be zero when the steady state exchange rate $\overline{s}$ equals the fundamental exchange rate $\overline{s^f}$

$$\overline{d^{SF}} = \overline{d^{LF}} = 0. \tag{20}$$

Thus, the fundamental steady state is characterized by zero demands for foreign currency, zero profits and equal selection of possible trading rules. Note, that this result can often be found in heterogeneous traders models of this type (see DeGrauwe and Grimaldi 2006).

What remains is to analyze if it is possible that the exchange rate remains in a state $\overline{s}$, where it is different from the fundamental exchange rate $\overline{s} \neq \overline{s^f}$. If this is the case, the fundamentalist traders' demand is always positive in absolute value. These orders will push the exchange rate back to the fundamental value. Thus, it is only possible that the exchange rate remains in a non-fundamental equilibrium $\overline{s} \neq \overline{s^f}$ if no trader uses the fundamental trading rules, that means $\overline{w^{SF}} = \overline{w^{LF}} = 0$ (see Grimaldi 2004). In line with Grimaldi (2004), any constant exchange rate can be an equilibrium if this condition is fulfilled. The reason is that there is no driving force that brings the exchange rate back to the fundamental equilibrium.

4 Calibration and Model Validation

In order use this artificial foreing exchange market as a computer laboratory for the analysis of regulatory policies we have to assume numerical values for the model's parameters first[11]. This set of used parameter values can be found in Table 1. Most of the parameter values are taken from Westerhoff (2008a). According to him, parameters are chosen such that the model is able to match numbers and statistics of real world financial market data[12]. Westerhoff (2008a) assumes both parameters to have the value 0.04. By following his suggestions short-term chartists expects a return of 0.04 percent for the next day in response to a return of 1 percent today and a cumulative return of 0.046 percent over the next 30 days. Fundamentalists, however, assume a return of 0.04 in response to a misalignment of 1 percent and a cumulative return of 0.71 over the next 30 days.

Westerhoff (2008a), Lux and Marchesi (2000), Lux (2009a) and Franke and Westerhoff (2009) validate agent-based models by analyzing how good the model is able to reproduce stylized facts of empirical daily financial market data like uncorrelated raw returns, volatility clustering, long memory and fat tails of the return distri-

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

[12] Studies that estimate rather than calibrate these models are Gilli and Winker (2003), Westerhoff and Reitz (2003), Lux (2006), Alfarano, Lux and Wagner (2005), Boswijk, Hommes and Manzan (2007), Winker, Gilli and Jeleskowic (2007), Manzan and Westerhoff (2007) and Ghongadze and Lux (2008). These studies suggest to that the chartist and fundamentalist reaction parameters κ^c and κ^f lie between 0 and 0.1 for daily data.

Table 1: Parameter Calibration

Parameter	Value	Interpretation
β	1.00	price adjustment
σ_s	0.01	non-fundamental news
σ_{s_f}	0.01	fundamental news
κ_C	0.04	chartists' reaction
σ_C	0.03	variety of chartist rules
κ_F	0.04	fundamentalists' reaction
σ_F	0.005	variety of fundamentalist rules
γ	800	intensity of choice
θ	0.985	memory parameter
N	30	longer term investment horizon

Note: Most prameter values are based on Westerhoff (2008a). We set a higher value for the intensity of choice parameter γ. The longer term investment horizon is assumed to be 30 days.

bution. Thus, we analyze how numbers and statistics like distributional moments, autocorrelations and distributional shape parameters of our generated computer laboratory data match numbers and statistics of data generated in the real world. If our models produces data whose properties are close to those of real world data, than we will - as proposed by Lux (2009a) - be able to perform an economic policy analysis which is close to reality. The economic policy analysis can be done by running the simulations for a given seed of random variables (!) but for different values of the policy parameter. More general results can be achieved by calculating average statistics over several simulation runs. These results can be interpreted as cross-section averages over several artificial financial markets.

Following Westerhoff (2008a) and Lux (2009a) we use the following validation criteria (Lux-Westerhoff criteria hereafter):

(i) *the model should generate bubbles and crashes (deviations from fundamental value),*

(ii) *asset prices should be more volatile than their fundamental values (excess volatility),*

(iii) *the return distribution should deviate from the normal distribution (excess kurtosis),*

(iv) *absence of autocorrelations in raw returns (non-predictability of daily returns),*

(v) *hyperbolically decaying autocorrelations of absolute returns (volatility clustering).*

Figure 1 contains results of the baseline simulation of our artificial foreign exchange market. The baseline simulation is characterized by the absence of transaction taxes. Moreover, the fundamental exchange rate is assumed to stay constant.

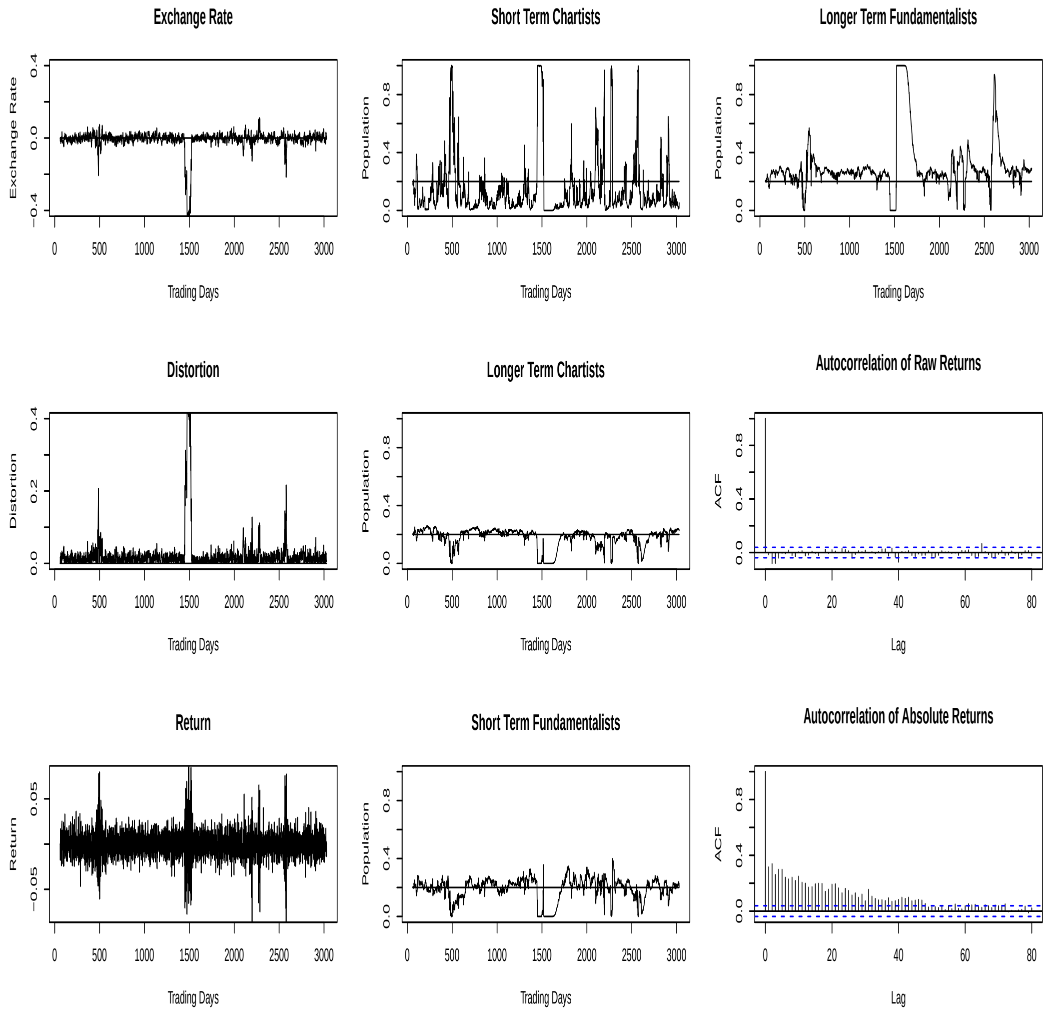

Figure 1: Simulation without Transaction Taxes

NOTE: Simulation of 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.01$. The fundamental value is assumed to be constant and normalized to zero. Distortion is measured as the absolute value of the deviation of the exchange rate from its fundamental value.

Table 2: Summary Statistics: Baseline Simulation versus Empirical Data

	Model	USD-Euro	YEN-USD	GBP-USD	USD-AusD
mean	0.000	0.000	0.000	0.000	0.000
st. dev.	0.015	0.007	0.007	0.006	0.009
skewness	0.000	0.179	-0.509	-0.330	-0.757
kurtosis	6.963	5.560	6.885	9.315	17.009

NOTE: Mean, variance, skewness and kurtosis are calculated from the model generated exchange rate return data by using the parameters given in table Table 1. The exchange rate data for the US-Dollar to Euro, Yen to US-Dollar, Great Brittain Pound to US-Dollar ans US-Dollar to Australian Dollar 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 and DEXAUUS.

Thus, fundamental based trading rules are not affected by the risk that the fundamental rate will change in the future. Fundamental risks make arbitrage more risky (Brunnermeier 2001) and thereby limit arbitrage. As a result, the fundamental trading rules may become less profitable, because fundamental forecasting rules generate larger prediction errors. We will tackle the problem of fundamental risks in section 5.2 and abstain from these kinds of risk during the baseline simulation.

From Figure 1 we can infer that most of the chartist traders prefer to be short term traders, while fundamental traders prefer the longer term investment horizon. This results is in line with the argument of Keynes (1936) and Tobin (1978) that short-term traders are destabilizing, while longer term traders are stabilizing. Moreover, this result is also in line with the empirical evidence from questionaire studies like Taylor and Allen (1992)[13]. There are periods with sharp increases in the number of short term chartist traders. These periods correspond to periods with high volatility and large misalignments in the exchange rate. Thus, short term chartists lead to additional risks. These periods of high volatility are followed by periods with a low volatility and a high popularity of the longer term fundamentalists trading strategy. Raw returns display two small negative autocorrelations. These mean reverting dynamics may result from the dominance of longer term fundamental traders who trade large orders against the mispricing. The autocorrelation function of absolute returns shows slowly decaying serial correlations in the magnitude of returns which correpond the the persistent phases of high and low volatility in the artificial return data. Summing up, the model is able to generate bubbles and crashes which can be inferred from the time series plot of misalignments (Figure 1). Moreover, it is able to generate non-predictable returns, which can be inferred from the small serial correlations in the artificial exchange rate returns. Furthermore, the models is able to generate volatility clustering. This, can be inferred by just eyeballing the time series of returns or more elaborate by the slowly decaying serial correlations in absolute returns. Moreover, within the model a return distribution emerges which

[13]See Menkhoff and Taylor (2007) for an survey article over questionaire studies in financial markets.

is characterized by excess kurtosis. As can be inferred from Table 2, the model is able to generate statistics, which are in line with the statistical properties of the Yen, Euro, the Great Britain Pound and the Australian Dollar versus US-Dollar daily exchange rate data. Note, that empirical data as well as data generated by our artificial foreign exchange market are characterized by zero means, standard deviations in the range of 0.006 to 0.015 and a kurtosis measures that ranges from 5.6 to 17.0. Thus, our model for daily exchange rate fluctuations can be regarded as validated by the Lux-Westerhoff criteria (Westerhoff 2008a, Lux 2009a). Moreover, we can conclude that all stylized facts remain under the introduction of longer term traders.

5 The Effectiveness of Transaction Taxes

Lux (2009a) and Westerhoff (2008a) suggest to use agent-based models as computer laboratories for performing economic policy experiments which are prohibitively costly to perform in real world markets. The advantages of agent-based modelling referred in Westerhoff (2008a) apply to the agent-based experiments presented in this paper in the following way:

(i) We are able to generate as much data points as needed for our policy analysis. In our agent-based policy analysis we choose following Westerhoff (2008a) a simulation horizon of 5000 data points, which correponds to a time horizon of 20 years since the model is calibrated to daily data. In more detail, we simulate 100 simulation runs of 5000 artificial trading days and take averages over all numbers and statistics for eauch value of the currency transaction tax. The advantage of this Monte-Carlo procedure is that our results do not only depend on one certain seed of random variables. One can interpret the generated sample as a panel of 100 foreign exchange markets over 5000 time steps.

(ii) Westerhoff (2008a) notes that the second advantage of agent-based modelling is that we are able to measure all variables precisely during our policy analysis. Within the agent-based experiments presented here we are able to measure the fundamental value as well as the decision of our artificial traders precisely.

(iii) We are able to control for exogenous shocks. Within our simulation we introduce three types of exogenous events. These are random deviations from the market makers price adjustment rule, fundamental news, and random deviations from the chartists' and fundamentalists' trading rules. Other exogenous events like a large drop in the fundamental value (e.g. a big recession) are not introduced. Thus, we analyze the effectiveness of the currency transaction tax during "normal" trading days.

(iv) We perform the simulations under the same conditions (the same seed of random variables), but with different values of the policy instrument. In this way we are able to get an inference on how the policy instrument changes

macroscopic properties - measured by numbers and statistics - of our artificial market. Westerhoff (2003a) and Westerhoff (2008a) suggests the following evaluation criteria

(a) volatility, defined as the average absolute change in the exchange rate

$$\text{Vol} = \frac{1}{T}\sum_{t=1}^{T} |s_t - s_{t-1}|, \tag{21}$$

and

(b) distortion

$$\text{Dis} = \frac{1}{T}\sum_{t=1}^{T} |s_t^f - s_t|, \tag{22}$$

which is defined as the average absolute deviation of the exchange rate s_t from its fundamental value s_t^f.

Moreover, Demary (2008) and Westerhoff (2008a) suggest to analyze the change the average percentage fraction of used trading rules as a measure of traders' behavior, which will change in response to policy changes, while Demary (2008) suggests also to analyze the change in the kurtosis of the exchange rate returns

$$\text{Kurt} = \frac{\frac{1}{T}\sum_{t=1}^{T}(s_t - s_{t-1})^4}{(\frac{1}{T}\sum_{t=1}^{T}(s_t - s_{t-1})^2)^2} \tag{23}$$

as a measure of catastrophic risks.

5.1 Simulations without Fundamental Risk

Figure 2 to 5 contains snapshorts of 3000 trading days within our artificial foreign exchange market. Figure 2 is based on a tax rate of 0.1 percent on each currency transaction, while Figure 3 and Figure 4 are based on the tax rates 0.3 and 0.5 percent, while Figure 5 is based on a tax rate of 1 percent. From Figure 2 one can infer by just visual inspection that bubbles and crashes, volatility clusters and distortions still prevail under a small transaction tax. Absolute returns are still characterized by persistent serial correlations. Similar to Figure 1 most of the traders prefer to be short-term chartist or longer term fundamentalist. Figure 3 shows a simulation run of our artificial foreign exchange market under a transaction tax rate of 0.3 percent. What can be seen is that short-term chartism now has the lowest popularity. The reason is that taxation makes this trading rule too expensive. The large fluctuations and amplitudes in short term chartist and longer term fundamentalists population fractions are now absent. As a result, the occurence of spectacular bubbles and crashes also diminishes, as can be inferred from the time series plot of distortions. Moreover, taxation reduces the autocorrelation of absolute returns. Thus, volatility clusters are absent under this tax rate. From Figure 4 and Figure 5 can be inferred that taxation of financial transactions smoothes the fluctuations in the popularity of trading rules. However, it seems that the highest stabilizing impact is achieved by increasing the tax rate from 0 to 0.1 percent.

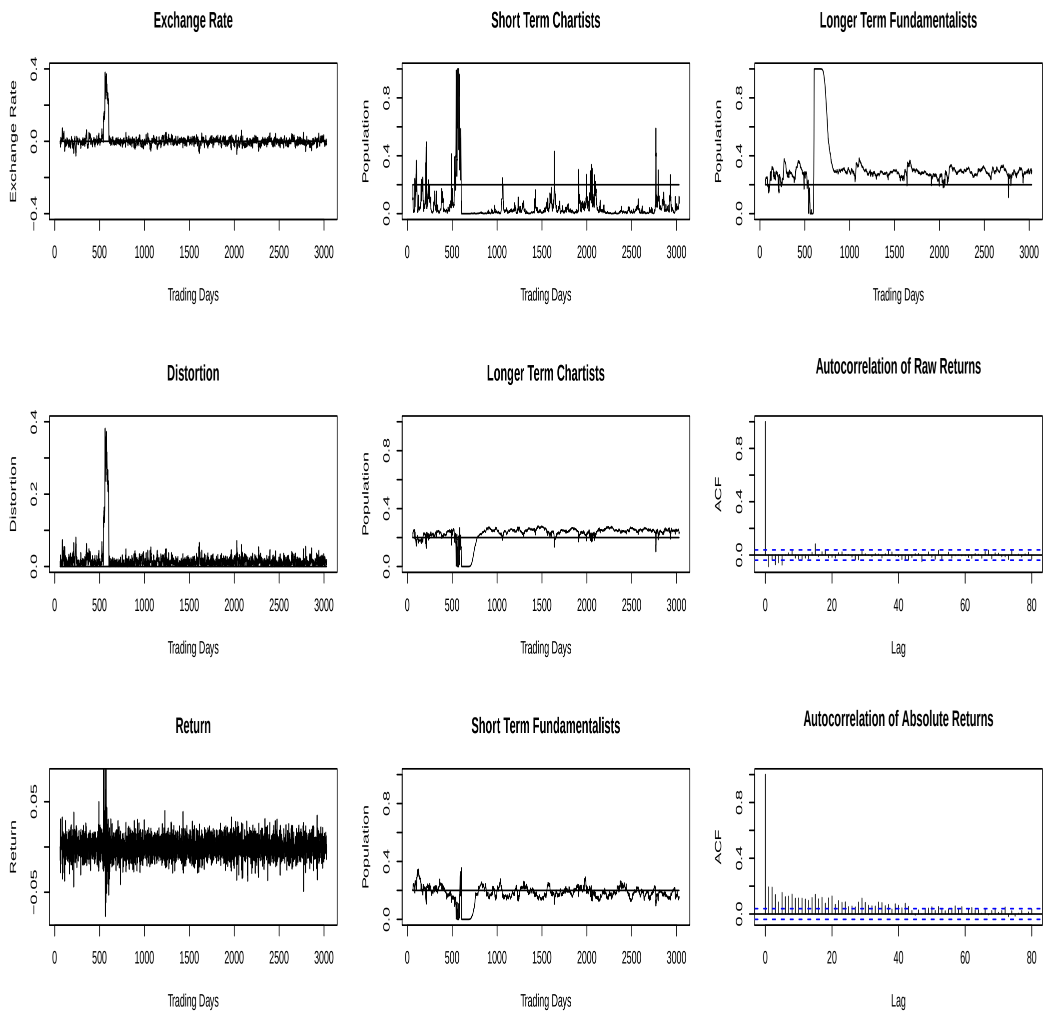

Figure 2: Simulation with a 0.1 Percent Transaction Tax Rate

NOTE: Simulation of 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.01$, $\sigma_c = 0.03$ and $\sigma_s = 0.01$. The fundamental value is normalized to zero. The transaction tax rate is 0.1 percent. Distortion is measured as the absolute value of the deviation of the exchange rate from its fundamental value.

Figure 6 contains summarized results of our policy experiments for small transaction taxes between 0 and 1 percent. Each reported number is the average over 5000 artificial trading days and 100 simulation runs. The simulations for different tax rates are based on the same seed of random variables. The tax rate is varied from 0 (the baseline case) in 0.1 percentage point steps and measured by the x-axis of the plot. As one can see, taxation of foreign currency transactions with small tax

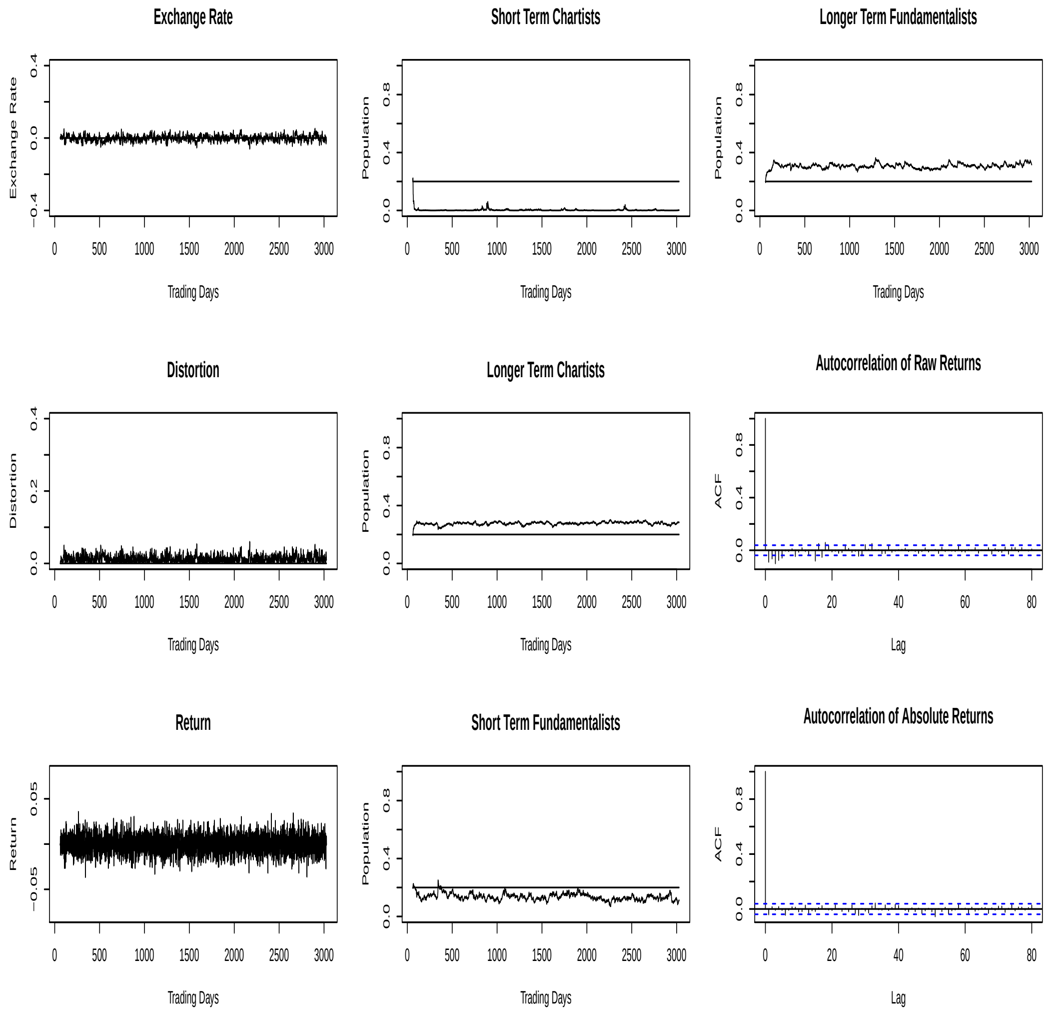

Figure 3: Simulation with a 0.3 Percent Transaction Tax Rate

NOTE: Simulation of 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.01$, $\sigma_c = 0.03$ and $\sigma_s = 0.01$. The fundamental value is normalized to zero. The transaction tax rate is 0.3 percent. Distortion is measured as the absolute value of the deviation of the exchange rate from its fundamental value.

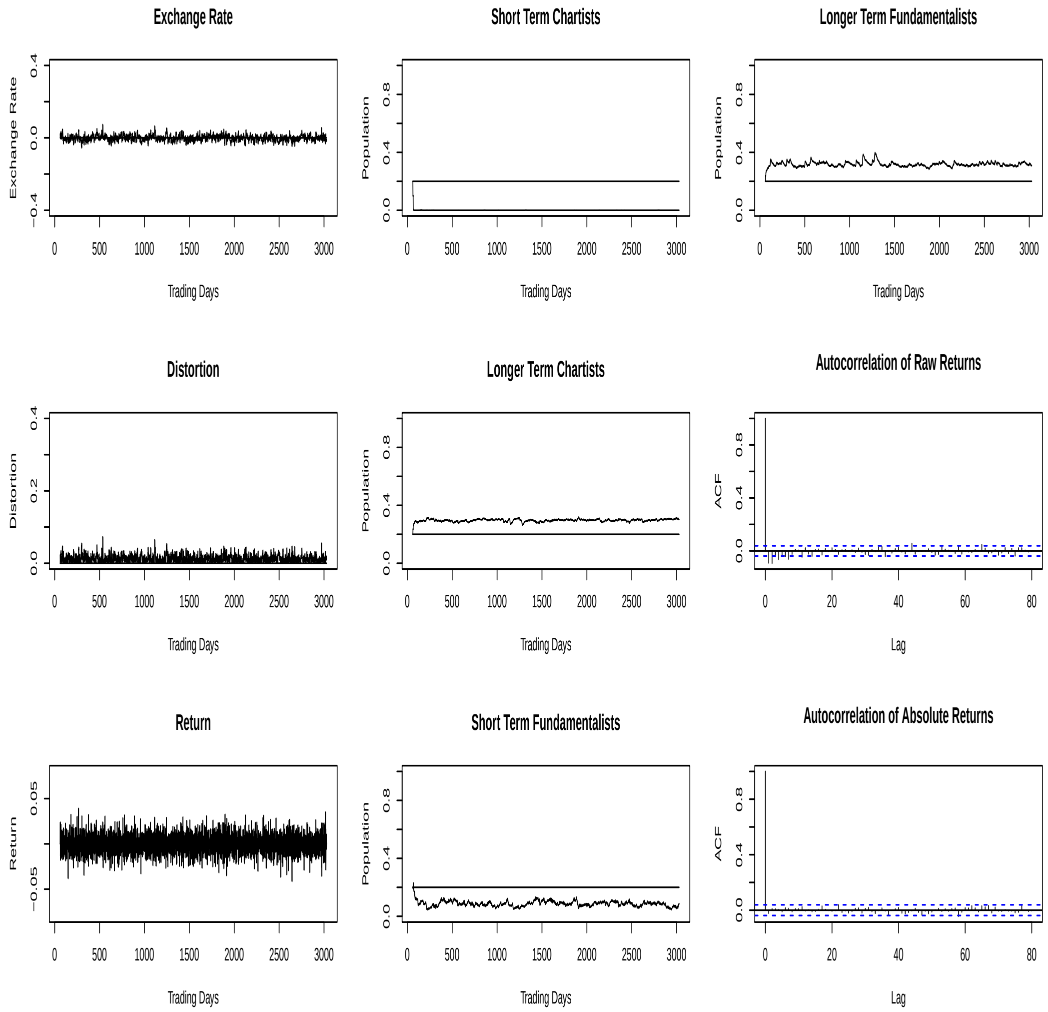

Figure 4: Simulation with a 0.5 Percent Transaction Tax Rate

NOTE: The numbers and statistics of this figure are based on 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.01$, $\sigma_c = 0.03$ and $\sigma_s = 0.01$. The fundamental value is normalized to zero. The transaction tax rate is 0.5 percent. Distortion is measured as the absolute value of the deviation of the exchange rate from its fundamental value.

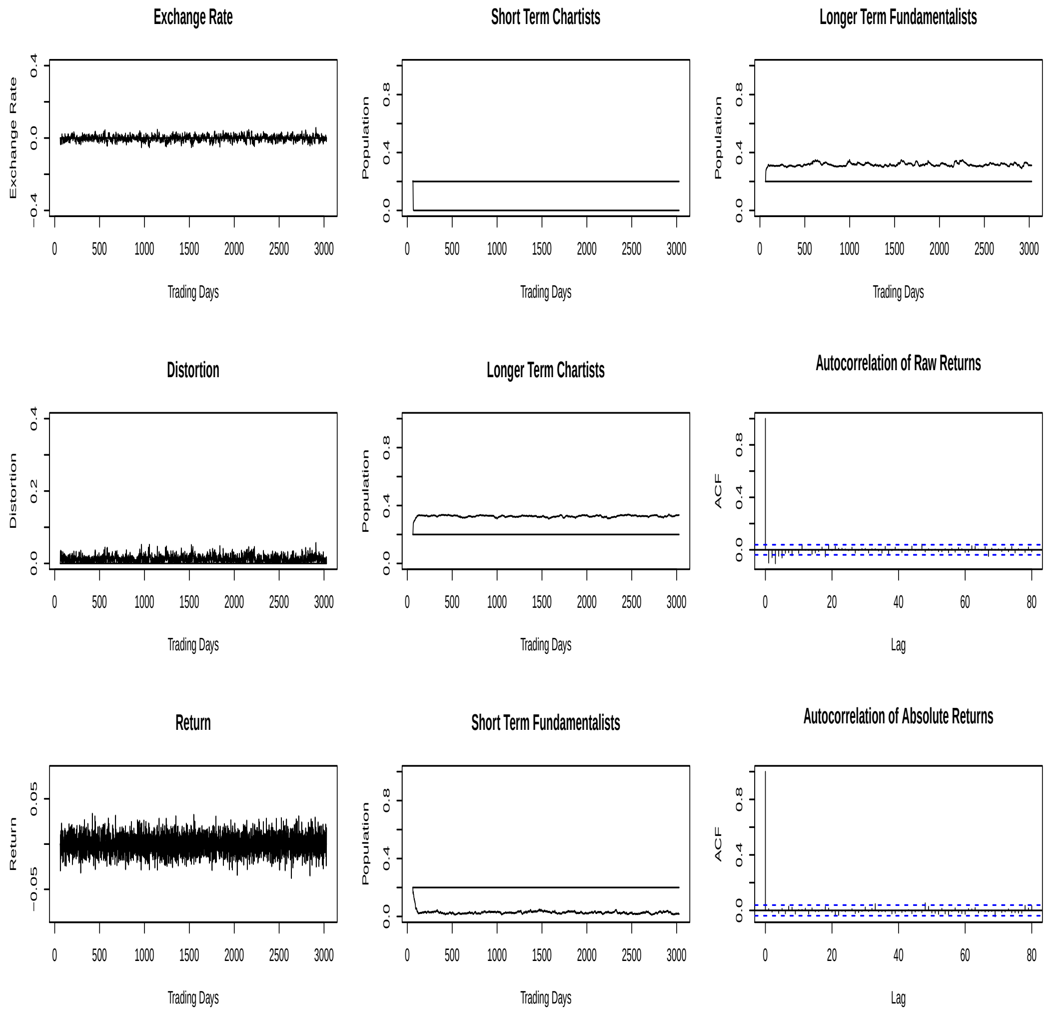

Figure 5: Simulation with a 1 Percent Transaction Tax

NOTE: Simulation of 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.01$, $\sigma_c = 0.03$ and $\sigma_s = 0.02$. The fundamental value is normalized to zero. The transaction tax rate is 1 percent. Distortion is measured as the absolute value of the deviation of the exchange rate from its fundamental value.

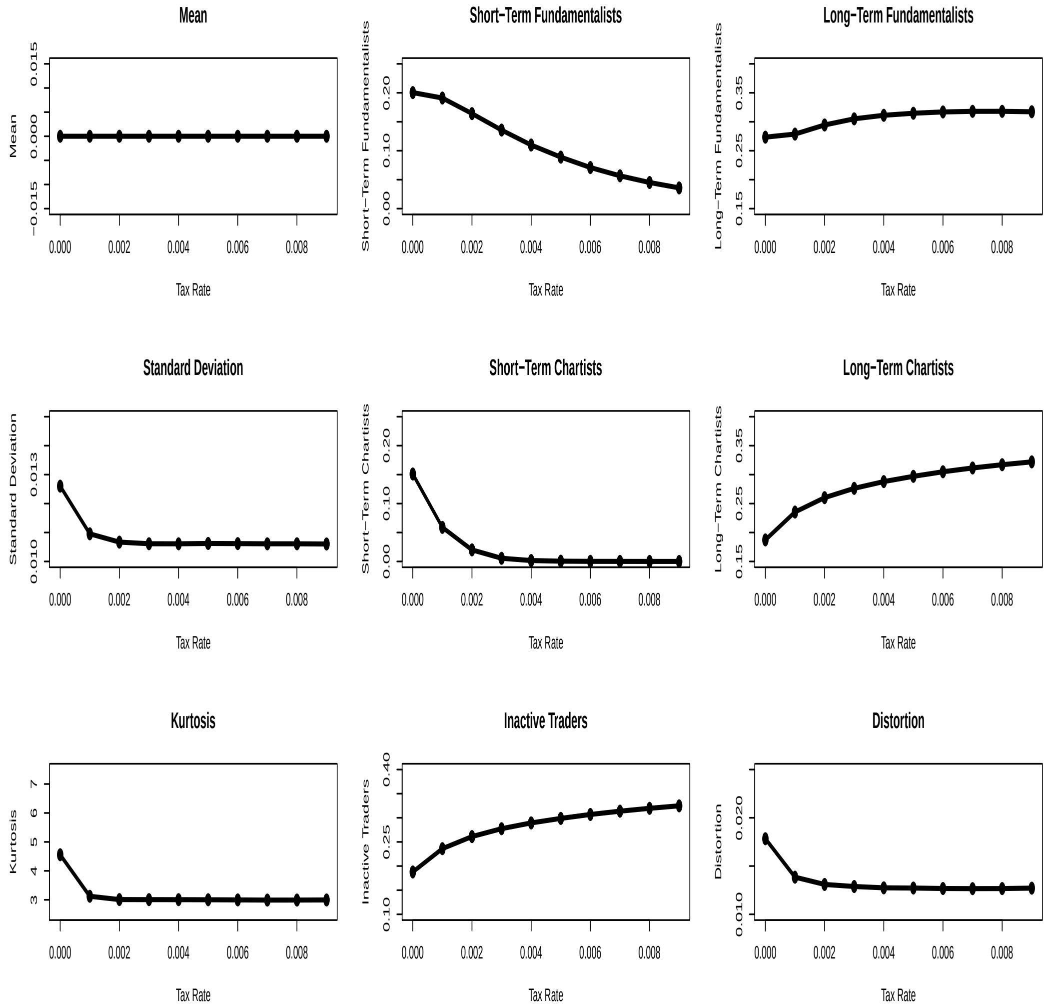

Figure 6: The Effectiveness of Small Currency Transaction Taxes

NOTE: The numbers and statistics of this figure are averages over 5000 artificial trading days over 100 simulation runs. They can be interpreted as averages over time and (artificial) markets. Note that all simulations for different values of the transaction tax rate are based on the same seed of random variables. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.01$. The fundamental value is normalized to zero. Distortion is defined as the average absolute deviation of the exchange rate from its fundamental value.

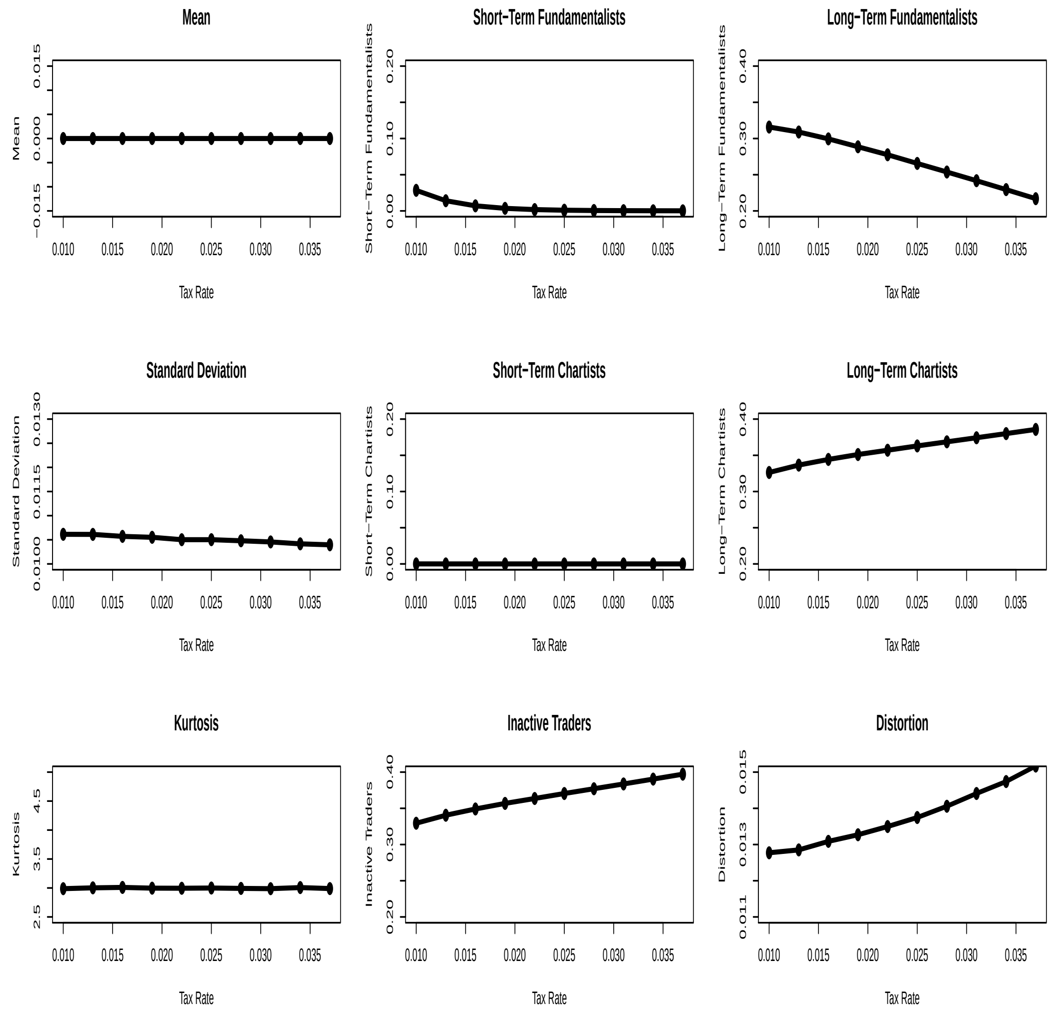

Figure 7: The Effectiveness of Higher Currency Transaction Taxes

NOTE: The numbers and statistics of this figure are averages 5000 artificial trading days over 100 simulation runs. They can be interpreted as averages over time and (artificial) markets. Note that all simulations for different values of the transaction tax rate are based on the same seed of random variables. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.02$. The fundamental value is normalized to zero. Distortion is defined as the average absolute deviation of the exchange rate from its fundamental value.

rates does not change the average returns on holding foreign currency. However, it decreases the volatility of exchange rate returns and the distortion of the market (the average misalignment). Thus, the transaction tax helps to decrease price volatility and brings the exchange rate on average closer to its fundamental value. However, the tax has no effect on the kurtosis of the exchange rate return distribution. The reason for this can be inferred from the change in the composition of used trading rules. The number of short-term chartists and short-term fundamentalists decreases to zero on average, while the number of longer-term chartists and longer-term fundamentalists is increasing. Moreover, the number of inactive traders is increasing because some short-term traders decide not to trade because transaction costs are higher than the returns of trading in the foreign exchange market. This is also the reason why the kurtosis of the exchange rate return distribution is not increasing. Suppose that all short-term traders switch to the longer-term trading strategies. This change in behavior will result in the fact that some traders place larger orders every 30 days instead of placing small orders every day. Because returns are proportional to market demand in our model, larger orders in a 30 days cycle lead to more frequent large returns and thus to a larger kurtosis of the return distribution. In the artificial foreign exchange market proposed by Demary (2008) a lot of traders change from short-term trading to longer term trading instead of becoming inactive. Therefore, the kurtosis of the exchange rate distribution increases in his simulations, which means a higher probability of large positive and negative returns. In the model presented here, however, enough short-term traders decide not to trade instead of becoming longer-term traders, which leads to the observed negligible effect of transaction taxes on the extreme parts of the return distribution measured by the kurtosis.

Figure 7 contains summary results for tax rates between 1 and 4 percent. As one can see, higher tax rates have no significant impact on the standard deviation and the kurtosis of the exchange rate returns. Within this interval for the tax rate the number of short-term chartists is zero, while the number of short-term fundamentalists declines to zero. For tax rates above 2.5 percent there are no short-term fundamentalists in the market. The number of inactive traders is monotonically increasing under these tax scenarios and lies between 30 and 40 percent. When the tax rate takes the value 4 percent, then 40 percent of the artificial traders decide not to trade. Moreover, it can be inferred that the number of longer term fundamentalists is decreasing under rising tax rates. While more than 30 percent of all traders use the longer term fundamentalist strategy for a tax rate of 1 percent, only 20 percent use this strategy for a tax rate of 4 percent. However, higher tax rates lead to a higher popularity of the longer term chartist trading rule. Under a 1 percent transaction tax approximately 30 percent of all traders use the longer term chartist rule, while approximately 40 percent use the chartist rule under a tax rate of 4 percent. The reason for the increasing popularity of the chartist rule is the following. Short term trading is prohibitively costly under these high tax rates. When there is no short-term trading, then high frequency fluctuations in the exchange rate are absent and longer lasting trends emerge. When there are longer lasting trends with less noise, then the longer term chartist forecasting technique becomes more precise and therefore more agents prefer to choose the chartist trading rule. Similar, longer term fundamentalist rules become more unprecise when the exchange rate exhibits longer lasting trends. As a result, which emerges from the changed composition of used trading rules, distortion is rising under higher tax rates. The reason is, that under higher tax rates chartist rules are more frequently used compared to fundamentalist trading rules. A similar result can also be found in Westerhoff (2003a). Furthermore, it can be inferred from Figure 7, that higher tax rates do not have any significant impact on volatility because the number of short-term traders is zero. In contrast to Demary (2008) higher tax rates do not have any impact on the kurtosis of the return distribution. As explained above, the kurtosis is increasing in his model because a lot of short-term traders decide to become longer term traders. This results in a higher frequency of larger orders which leads to a higher kurtosis of the return distribution. In this model, however, 40 percent of all traders decide not to trade instead of becoming longer term traders. Thus, higher tax rates have no significant impact on the kurtosis of the return distribution here.

5.2 Simulations under Fundamental Risk

In Figure 8 the fundamental exchange rate is assumed to follow a random walk $s^f_{t+1} = s^f_t + 0.01\varepsilon_{t+1}$, where ε_t is standard normally distributed fundamental news. When the fundamental rate follows a random walk, then the fundamental-based trading strategies becomes more risky. The reason is that fundamentalists can only assume that the exchange rate changes in order to correct to the fundamental rate s^f_t, because it is the best forecast of the uncertain future fundamental rate s^f_{t+N}. When there is a large fundamental innovation, then fundamentalists make a large prediction error. As a consequence, fundamentalists lose money which may result in a higher popularity of chartist rules for the next period. Brunnermeier (2001) notes that this fundamental risk limits arbitrage and in this way leads to persistent speculative bubbles. From Figure 8 can be inferred, that similar to the simulations without fundamental risk most of the chartist traders are short term traders, while most of the fundamentalists are long term traders. Again, periods with a clear dominance of chartist traders correspond to periods with large fluctuations in the exchange rate and large misalignments. These periods are followed by longer correction periods with a clear dominance of longer term fundamentalist traders. The emergent properties are again excess kurtosis of the return distribution and volatility clustering, which can be inferred from the slowly decaying autocorrelations of absolute returns. In contrast to the simulations without fundamental risk, raw returns seem to exhibit more persistent autocorrelations.

Figure 9 contains simulation results of our artificial foreign exchange market with fundamental risk in which a policy maker introduces a currency transaction tax rate of 0.5 percent. Under taxation short term chartism becomes unprofitable, thus, the number of traders who use this trading rule becomes zero over the whole simulation horizon. In reaction to missing chartists misalignments diminish, which is the reason for the diminishing periods with a clear dominance of longer term fundamental traders. Short term fundamentalism also becomes unprofitable, however, longer term chartism rises in popularity compared to the case without taxation. Emergent properties from this changed interaction are diminishing autocorrelations of raw

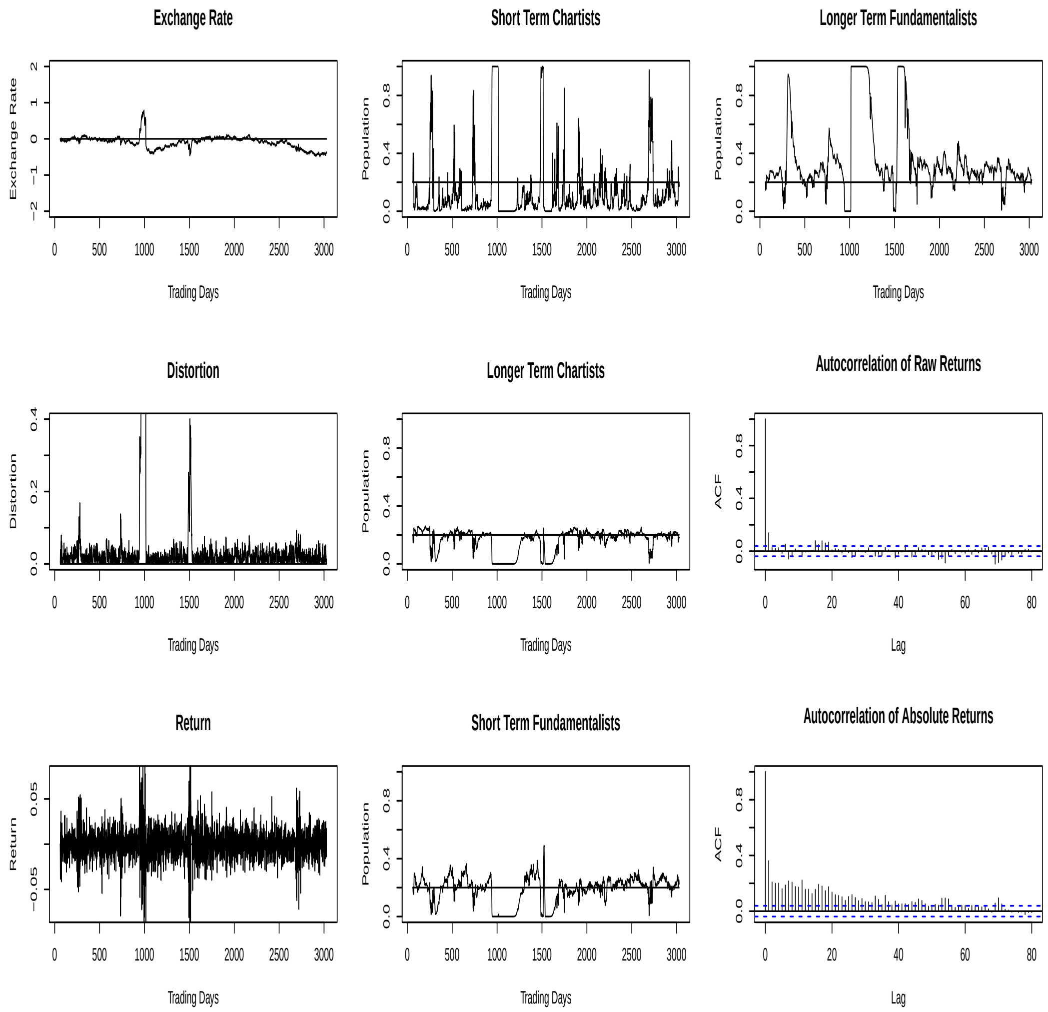

Figure 8: Simulation with Fundamental Risk and no Transaction Taxes

NOTE: Simulation of 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.02$. The fundamental value is normalized to zero. The transaction tax rate is 0 percent.

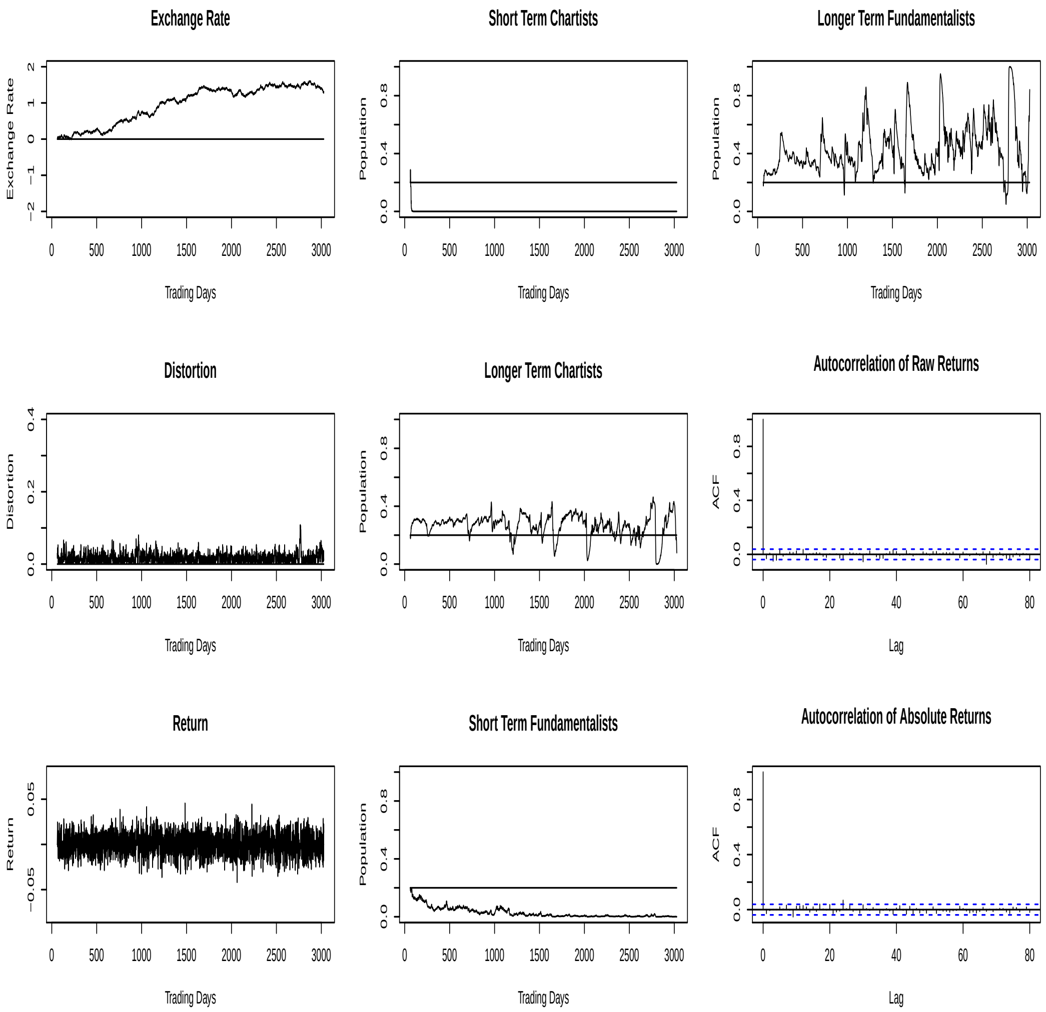

Figure 9: Simulation with Fundamental Risk and a 0.5 percent Transaction Tax

Note: Simulation of 3000 artificial trading days. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.02$. The fundamental value is normalized to zero. The transaction tax rate is 0.5 percent. Distortion is defined as the absolute deviation of the exchange rate from its fundamental value.

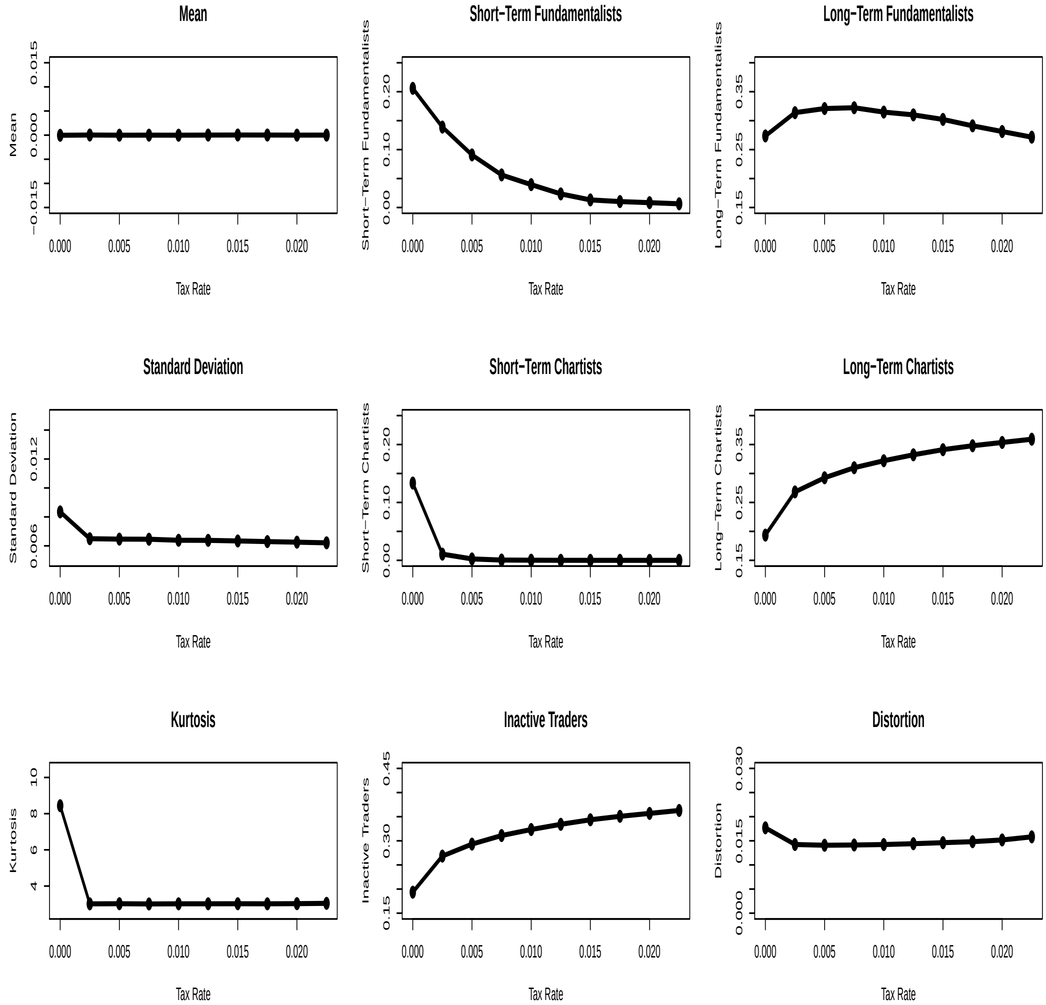

Figure 10: The Effectiveness of Small Transaction Taxes under Fundamental Risk

NOTE: The numbers and statistics of this figure are averages over 5000 artificial trading days over 100 simulation runs. They can be interpreted as averages over time and (artificial) markets. Note that all simulations for different values of the transaction tax rate are based on the same seed of random variables. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.02$. Distortion is defined as the average absolute deviation of the exchange rate from its fundamental value.

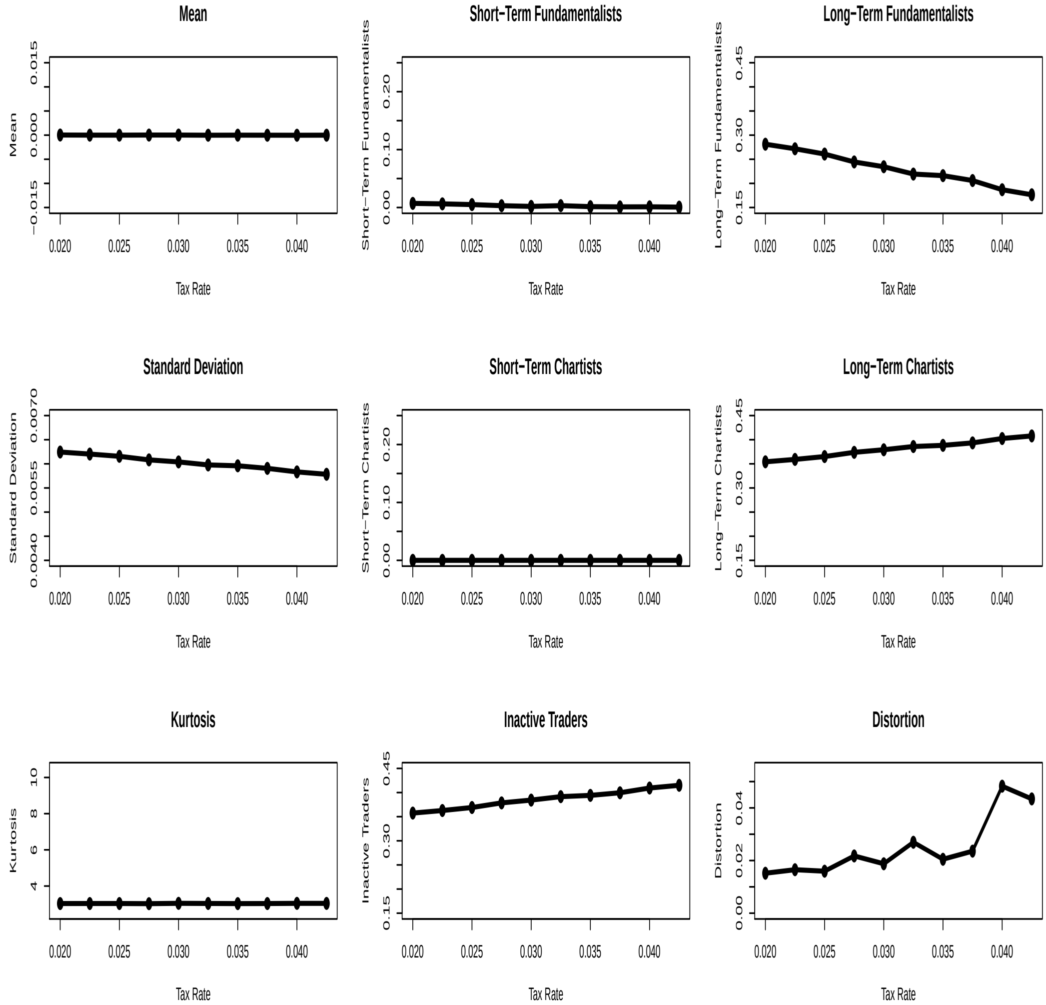

Figure 11: The Effectiveness of Higher Transaction Taxes under Fundamental Risk

NOTE: The numbers and statistics of this figure are averages over 5000 artificial trading days over 100 simulation runs. They can be interpreted as averages over time and (artificial) markets. Note that all simulations for different values of the transaction tax rate are based on the same seed of random variables. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.01$. Distortion is defined as the average absolute deviation of the exchange rate from its fundamental value.

returns and diminishing autocorrelations of absolute returns. Thus, under taxation volatility clusters diminish. Moreover, the misaligments decrease in amplitude.

Figure 10 contains figures with summary statistics over 100 simulation runs of size 5000. These can be interpreted as statistics over a panel of 100 artificial markets and 5000 trading days. These summary statistics are plotted for different values of the currency transaction tax rate. Similar to other configurations taxation does not change average daily returns. The standard deviation of returns and the kurtosis of the return distribution are decreasing under taxation. The lower kurtosis measure is due to the diminishing volatility clusters under taxation. Taxation of round trips increases the costs of speculation. In response the number of inactive traders is increasing in the transaction tax rate. As already indicated in Figure 8, the number of short term fundamentalists and short term chartists are decreasing in the tax rate, while the number of longer term chartists and longer term fundamentalists is at least for small tax rates increasing. Note, that the response of longer term fundamentalist traders is hump-shaped again. For tax rates below 0.5 percent the number of longer term term fundamentalists is increasing, while fundamentalists decrease in number when transaction taxes are higher than 0.5 percent. However, the number of longer term chartist traders is monotonically increasing in the currency transaction tax rate. The rationale is the following. Under taxation the number of short-term traders decrease in magnitude, which leads to less short-term fluctuations in the exchange rate. Thus, longer lasting trends in the exchange rate emerge, which make the longer term chartist trading rule more profitable compared to the longer term fundamentalist rule. As can be inferred from Figure 11 misalignments increase for tax rates above 2 percent. This u-shaped response of misalignment are similar to Westerhoff (2003a, 2008a) due to the fact that the number of longer term chartists is increasing in the transaction tax rate, while the number of fundamentalists rises for small tax rates, while the popularity of this trading strategy decreases in number for higher tax rates.

5.3 Sensitivity Analysis

Table 3 contains results of a sensitivity analysis. The reported numbers and statistics are averages over 5000 artificial trading days and 50 simulation runs. We report the volatility and the distortion for the tax rates $\tau \in \{0.0\%, 1.0\%, 2.0\%, 3.0\%, 4.0\%\}$ and for different calibrations of the model's parameters like the fundamentalists' misalignment-correction parameter $\kappa_F \in \{0.02, 0.04, 0.06, 0.08\}$, the chartists' trend-extrapolation parameter $\kappa_C \in \{0.02, 0.04, 0.06, 0.08\}$, the intensity of choice parameter $\gamma \in \{400, 600, 800, 1000\}$, the memory parameter $\theta \in \{0.75, 0.80, 0.975, 0.985\}$ and the longer term traders investment horizon $N \in \{1, 10, 20, 30\}$.

Panel I contains the sensitivity analysis under a constant fundamental value, while the results in panel II are based on the assumption that the fundamental value follows a random walk. From panel I we can infer that the volatility seems to be robust for different calibrations of the model. It is slighlty declining in the tax rate for all 20 calibrations. Results for the distortion are robust for tax rates below 3.0% at least for variations in the fundamentalist and chartist behavioral parameters as well as for the memory parameter and the intensity of choice parameter.

Table 3: Sensitivity Analysis

	I: Constant Fundamental Value									
	Volatility					Distortion				
Tax Rate	0.0%	1.0%	2.0%	3.0%	4.0%	0.0%	1.0%	2.0%	3.0%	4.0%
$\kappa^F = 0.02$	0.013	0.011	0.010	0.010	0.010	0.018	0.013	0.014	0.016	0.083
$\kappa^F = 0.04$	0.012	0.011	0.010	0.010	0.010	0.019	0.013	0.014	0.016	0.068
$\kappa^F = 0.06$	0.012	0.011	0.010	0.010	0.010	0.018	0.013	0.014	0.016	0.041
$\kappa^F = 0.08$	0.013	0.011	0.010	0.010	0.010	0.018	0.013	0.014	0.016	0.061
$\kappa^C = 0.02$	0.012	0.011	0.010	0.010	0.010	0.016	0.013	0.014	0.020	0.075
$\kappa^C = 0.04$	0.012	0.011	0.010	0.010	0.010	0.017	0.013	0.014	0.016	0.092
$\kappa^C = 0.06$	0.013	0.011	0.010	0.010	0.010	0.018	0.013	0.014	0.016	0.053
$\kappa^C = 0.08$	—	0.011	0.010	0.010	0.010	—	0.013	0.014	0.016	0.055
$\gamma = 400$	0.012	0.011	0.011	0.011	0.011	0.016	0.013	0.013	0.013	0.014
$\gamma = 600$	0.012	0.011	0.011	0.011	0.010	0.017	0.013	0.013	0.014	0.015
$\gamma = 800$	0.013	0.011	0.011	0.010	0.010	0.017	0.013	0.013	0.014	0.016
$\gamma = 1000$	0.013	0.011	0.011	0.010	0.010	0.020	0.013	0.014	0.015	0.017
$\theta = 0.750$	0.012	0.011	0.011	0.011	0.011	0.018	0.014	0.014	0.013	0.013
$\theta = 0.800$	0.012	0.011	0.011	0.011	0.011	0.018	0.014	0.013	0.013	0.013
$\theta = 0.975$	0.013	0.011	0.011	0.010	0.010	0.018	0.013	0.013	0.014	0.016
$\theta = 0.985$	0.013	0.011	0.010	0.010	0.010	0.018	0.013	0.014	0.016	0.052
$N = 1$	0.014	0.010	0.010	0.010	0.010	0.069	0.323	0.364	0.426	0.360
$N = 10$	0.013	0.010	0.010	0.010	0.010	0.025	0.018	0.053	0.224	0.336
$N = 20$	0.013	0.010	0.010	0.010	0.010	0.020	0.014	0.015	0.017	0.046
$N = 30$	0.013	0.011	0.011	0.010	0.010	0.018	0.013	0.013	0.014	0.016
	II: Fundamental Value Follows Random Walk									
	Volatility					Distortion				
Tax Rate	0.0%	1.0%	2.0%	3.0%	4.0%	0.0%	1.0%	2.0%	3.0%	4.0%
$\kappa^F = 0.02$	0.013	0.011	0.011	0.011	0.010	0.019	0.014	0.016	0.023	0.081
$\kappa^F = 0.04$	0.012	0.011	0.011	0.011	0.010	0.018	0.014	0.017	0.019	0.101
$\kappa^F = 0.06$	0.013	0.011	0.011	0.011	0.010	0.018	0.014	0.016	0.021	0.109
$\kappa^F = 0.08$	0.013	0.011	0.011	0.011	0.010	0.019	0.014	0.016	0.019	0.095
$\kappa^C = 0.02$	0.013	0.011	0.011	0.010	0.010	0.018	0.014	0.016	0.023	0.068
$\kappa^C = 0.04$	0.013	0.011	0.011	0.010	0.010	0.019	0.014	0.016	0.024	0.111
$\kappa^C = 0.06$	0.013	0.011	0.011	0.010	0.010	0.019	0.014	0.016	0.030	0.139
$\kappa^C = 0.08$	—	0.011	0.011	0.010	0.010	—	0.014	0.016	0.026	0.091
$\gamma = 400$	0.012	0.011	0.011	0.011	0.010	0.017	0.014	0.015	0.016	0.017
$\gamma = 600$	0.012	0.011	0.011	0.011	0.010	0.018	0.014	0.015	0.017	0.023
$\gamma = 800$	0.013	0.011	0.011	0.010	0.010	0.018	0.014	0.016	0.021	0.101
$\gamma = 1000$	—	0.011	0.011	0.010	0.010	—	0.014	0.017	0.040	0.203
$\theta = 0.750$	0.012	0.011	0.011	0.011	0.011	0.019	0.016	0.015	0.015	0.015
$\theta = 0.800$	0.012	0.011	0.011	0.011	0.011	0.020	0.016	0.015	0.015	0.015
$\theta = 0.975$	0.013	0.011	0.011	0.011	0.010	0.019	0.014	0.015	0.016	0.021
$\theta = 0.985$	—	0.011	0.011	0.010	0.010	—	0.014	0.016	0.031	0.115
$N = 1$	0.015	0.010	0.010	0.010	0.010	0.084	0.417	0.439	0.431	0.452
$N = 10$	0.013	0.010	0.010	0.010	0.010	0.024	0.021	0.236	0.375	0.410
$N = 20$	0.013	0.011	0.010	0.010	0.010	0.020	0.015	0.018	0.119	0.346
$N = 30$	0.013	0.011	0.011	0.010	0.010	0.019	0.014	0.016	0.020	0.115

Note: The numbers and statistics are averages over 5000 artificial trading days over 50 simulations runs. Note that all simulations for different values of the transaction tax rate are based on the same seed of random variables. The underlying parameter values are $\kappa_f = \kappa_c = 0.04$, $N = 30$, $\gamma = 800$, $\theta = 0.975$, $\sigma_f = 0.005$, $\sigma_c = 0.03$ and $\sigma_s = 0.005$ except otherwise stated.

For tax rate above 3.0% we find that values of the distortion measure vary with changes in the calibration. Interestingly, we find that the u-shaped reaction of the distortion measure to changes in the tax rate is robust to all 20 parameterizations. However, the convexity of this curve is smaller for higher values of the chartists' and fundamentalists' behavioral parameters as well as for smaller intensity of choice parameters and smaller memory parameter values. Thus, mispricings are reduced when fundamentalist traders as well as chartist traders act more aggressively. Moreover, we find that the convexity of the distortion-tax-curve is smaller, the higher the longer term traders' investment horizon. Furthermore, the distortion is smaller in value for longer investment horizons. This finding is robust for all tax rates considered here. This findings also hold, when we assume the fundamental value to follow a random walk (panel II). Thus, traders with longer investement horizons act as a stabilizing force as claimed by Keynes (1936) and Tobin (1978). We conclude, that the finding that small tax rates decrease distortion, while higher tax rates increase it is a robust finding for 20 calibrations of this agent-based financial market model.

6 Conclusion

Agent-based models with heterogeneous interacting agents are powerful tools for economic policy analysis. Their success in replicating stylized facts of financial markets data like bubbling and crashing asset prices, non-predictability of returns, excessively high volatilities of returns, excessively high probabilities of extreme large absolute returns and volatility clustering makes them preferable tools for analyzing regulations in financial markets. The empirical stylized facts emerge within agent-based models from the interaction of heterogeneous traders. By affecting the individual agents decisions by market regulations, these regulations have effects on emergent properties like the ones cited before which cannot simply be deduced by aggregating over individual agents.

Within this paper we introduced the longer term traders of Demary (2008a) into the foreign exchange market model proposed by Westerhoff (2008a). Our first result is that the stylized facts of financial market data also emerge when longer term traders are introduced into these models. Because our model is able to reproduce stylized facts of financial market data, we regard is as validated by the Lux-Westerhoff criteria (Lux 2009a and Westerhoff 2008). The success of this artificial foreign exchange market in replicating stylized facts of foreign exchange market data makes it a powerful tool for analyzing the following proposition which is often heard from the proponents of financial market taxes and the public media in times of financial instability: *transaction taxes stabilize financial markets by crowding out short-term traders in favor of longer term investors.*

The economic policy analysis leads to the following results.

(i) Small transaction taxes make short-term trading unprofitable. Therefore, the number of short-term fundamentalists and short-term chartists decreases to zero. One emergent property of this change in behavior are the diminishing volatility clusters. Moreover, volatility and distortions decrease under small transaction taxes. The reason for this result lies in the fact that under small

transaction taxes the market is populated by a higher number of longer term fundamentalist traders compared to longer term chartist traders.

(ii) However, when tax rates are too high, misalignments increase as also found in Westerhoff (2003a, 2008a). The reason for this u-shaped response of misaligments to increasing tax rates is caused by the changed composition of used trading rules. In his model tax rates above a certain threshold make fundamental trading unprofitable relative to trend-chasing trading. Within our artificial foreign exchange market a similar result emerges. Here, the longer term fundamentalist trading rule becomes unpopular under tax rates above a certain threshold, while the number of traders, who favor the longer term chartist trading rule increases. In contrast to Keynes (1936) and Tobin (1978) taxing financial markets is not *per se* stabilizing by making short-term trading unprofitable in favor of longer term trading. Our model shows that this result is not independent of the composition of the used trading rules in the financial market and not independent of the tax rate.

(iii) A sensitivity analysis indicates that these findings are robust for 20 different calibrations of the model. Furthermore, it indicates that higher investment horizons of longer term traders lead to less misalignments. We conclude that longer term traders act as a stabilizing force within this model.

This model shows that taxing financial markets has complex effects caused by behavioral heterogeneity and interaction of agents and therefore policy makers should pay attention on recent research in the area of agent-based financial market models. Within a world in which heterogeneous agents interact the effects of currency transaction taxes are complex and their effects on markets emerge from the change in the composition of popular trading rules in the market. The stabilizing or destabilizing effects of regulatory policies thus emerge by changing the composition of used trading rules. This study and Westerhoff (2003a, 2008a) come to the result that there is a threshold tax rate where transaction taxes becomes destabilizing. Because this threshold is not known in reality introducing a tax rate on financial transactions which is above this threshold may have destabilizing effects. Moreover, when a policy maker wants to set a tax rate below this threshold, he or she has to consider other transaction costs in the financial market. Therefore, the tax threshold might be lower in reality due to additional transaction costs. Furthermore, Demary (2008) finds that the kurtosis of the return distribution may increase due to taxation because agents trade large orders instead of a sequence of smaller orders. This results may also emerge in similar agent-based financial market models, when it is more profitable for traders to change to longer term trading rules instead of deciding not to trade. Furthermore Pelizzari and Westerhoff (2007) find that the effectiveness of transaction taxes depends on the underlying market microstructure. During phases of financial instability policy makers are often tempted to the introduction of financial market taxes. Recent research, like this study and the papers cited therein show, that changes in the composition in trading rules has important consequences for the effectiveness of financial market taxes. Therefore policy makers should be aware of setting the wrong tax rate. The Swedish experience with transaction taxes was caused by tax rates, which were simply set too high. Agent-based models may therefore give important insights into the working of financial market regulations.

References

[1] Alfarano, S., T. Lux and F. Wager (2005), "Estimation of Agent-Based Models: The Case of an Asymmetric Herding Model", *Computational Economics*, Vol. 26, 19-49.

[2] Aliber R., B. Chowdry and S. Yan (2005), "Some Evidence that a Tobin Tax on Foreign Exchange Transactions May Increase Volatility", *European Finance Review*, Vol. 7, 481-510.

[3] Boswijk, P., C. Hommes and S. Manzan (2007), "Behavioral Heterogeneity in Stock Prices", *Journal of Economi Dynamics and Control*, Vol. 31, 1938-1970.

[4] Brock, W. and C. Hommes (1998), "Heterogeneous Beliefs and Routes to Chaos in a Simple Asset Pricing Model", *Journal of Economic Dynamics and Control*, Vol. 22, 1235-1274.

[5] Brunnermeier, M. (2001), "*Asset Pricing under Asymmetric Information: Bubbles, Crashes, Technical Analysis and Herding*", Oxford University Press, Oxford.

[6] Chiarella, C. (1992), "The Dynamics of Speculative Behavior", *Annals of Operations Research*, Vol. 37, 101-123.

[7] Chiarella, C. and X. He (2002), "An Adaptive Model of Asset Pricing and Wealth Dynamics with Heterogeneous Trading Strategies", *Computing in Economics and Finance*, Vol. 135, Society for Computational Economics.

[8] Day, R. and W. Huang (1990), "Bulls, Bear and Market Sheep", *Journal of Economic Behavior and Organization*, Vol. 14, 299-329.

[9] DeGrauwe, P. and M. Grimaldi (2006), "Exchange Rate Puzzles: A Tale of Switching Attractors", *European Economic Review*, Vol. 50, 1-33.

[10] Demary, M. (2008), "Who Does a Currency Transaction Tax Harm More: Short-term Speculators or Long-term Investors?", *Jahrbücher für Nationalökonomie und Statistik*, Vol. 228, 228-250.

[11] Engel, C. and J. Hamilton (2000), "Long Swings in the Dollar. Are They in the Data and Do the Markets Know It?", *American Economic Review*, Vol. 80, 689-713.

[12] Farmer, D. and S. Joshi (2002), "The Price Dynamics of Common Trading Strategies", *Journal of Economic Behavior and Organization*, Vol. 49, 149-171.

[13] Franke, R. and F. Westerhoff (2009), "Validation of a Structural Stochastic Volatility Model of Asset Pricing", Working Paper.

[14] Gilli, M. and P. Winker (2003), "A Global Optimization Heuristic for Estimating Agent-Based Models", *Computational Statistics and Data Analysis*, Vol. 42, 299-312.

[15] Ghongadze, J. and T. Lux (2009), "Modelling the Dynamics of EU Economic Sentiment Indicators: An Interaction-Based Approach", Kiel Working Papers No. 1482, Kiel Institute for the World Economy.

[16] Grimaldi, M. (2004), "*The Exchange Rate, Heterogeneity of Agents and Bounded Rationality*", Dissertation, Katholieke Universiteit Leuven.

[17] Haber, G. (2008), "Monetary and Fiscal Policy Analysis With an Agent-Based Macroeconomic Model", Jahrbücher für Nationalökonomie und Statistik, Vol. 228(2+3), 276-295.

[18] Hau, H. (2006), "The Role of Transaction Costs for Financial Volatility: Evidence from the Paris Bourse", *Journal of the European Economic Association*, Vol. 4, 862-890.

[19] Hommes, C. (2006), "Heterogeneous Agents Models in Economics and Finance", in: L. Tesfatsion and K. Judd (eds.), "*Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics*", North-Holland, Amsterdam, 1107-1186.

[20] Jones, C. and P. Seguin (1997), "Transaction Costs and Price Volatility: Evidence from Commission Deregulation", *American Economic Review*, Vol. 87, 728-737.

[21] Keynes, J. M. (1936), "*The General Theory of Employment, Interest and Money*", New York.

[22] Kirman, A. (1991), "Epidemics of Opinion and Speculative Bubbles in Financial Markets", in: Taylor, M. (ed.), "*Money and Financial Markets*", Oxford, 354-386.

[23] LeBaron, B. (1999), "Technical Trading Rule Profitability and Foreign Exchange Intervention", *Journal of International Economics*, Vol. 49, 125-143.

[24] LeBaron, B. (2006), "Agent-Based Computational Finance", in: in: L. Tesfatsion and K. Judd (eds.), "*Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics*", North-Holland, Amsterdam, 1187-1233.

[25] LeRoy, S. and R. Porter (1981), "The Present Value Relation: Tests Based on Implied Variance Bounds", *Econometrica*, Vol. 64, 555-574.

[26] Lux, T. (1995), "Herd Behavior, Bubbles and Crashes", *Economic Journal*, Vol. 105, 881-896.

[27] Lux, T. and M. Marchesi (1999), "Scaling and Criticality in a Stochastic Multi-Agent of a Financial Market", Nature, Vol. 397, 498-500.

[28] Lux, T. and M. Marchesi (2000), "Volatility Clustering in Financial Markets: A Microsimulation of Interacting Agents", International Journal of Finance and Economics, Vol. 3, 675-702.

[29] Lux, T. (2006), "Rational Forecasts or Social Opinion Dynamics? Identification of Interaction Effects in a Business Climate Survey", Manuscript, University of Kiel.

[30] Lux, T. (2009a), "Stochastic Behavioral Asset Pricing Models and the Stylized Facts", in: Hens, Thorsten and Klaus Schenk-Hoppé (eds.) "*Handbook of Financial Markets: Dynamics and Evolution*", North Holland: Amsterdam, 161-211.

[31] Lux, T. (2009b), "Applications of Statistical Physics in Finance and Economics", in: Rosser, J.B., Jr. (ed.), "*Handbook of Complexity Research*", Cheltenham.

[32] Manski, C. and D. McFadden (1981), "*Structural Analysis of Discrete Data with Econometric Applications*", Cambridge.

[33] Manzan, S. and F. Westerhoff (2007), "Heterogeneous Expectations, Exchange Rate Dynamics and Predictability", *Journal of Economic Behavior and Organization*, Vol. 64, 111-128.

[34] Menkhoff, L. and M. Taylor (2007), "The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis", *Journal of Economic Literature*, Vol. XLV (December), 936-972.

[35] Pelizzari, P. and F. Westerhoff (2007), "Some Effects of Transaction Taxes under Different Market Microstructures", *Quantitative Finance Research Center*, Research Paper 212.

[36] R Development Core Team (2009), "R: A Language and Environment for Statistical Computing", R Foundation for Statistical Computing, Vienna, Austria, http://www.R-project.org.

[37] Shiller, R. (1981), "Do Stock Prices Move to Much to be Justified by subsequent Changes in Dividents", American Economic Review, Vol. 71(3), 421-436.

[38] Taylor, M. and H. Allen (1992), "The Use of Technical Analysis in the Foreign Exchange Market", *Journal of International Money and Finance*, vol. 11, 304-314.

[39] Tobin, J. (1978), "A Proposal for International Monetary Reform", *Eastern Economic Journal*, Vol. 4, 153-159.

[40] Umlauf, S. (1993), "Transaction Taxes and the Behavior of the Swedish Stock Market", *Journal of Financial Economics*, Vol. 33, 227-240.

[41] Weidlich, A. and D. Veit (2008), "Agent-Based Simulations for Electricity Market Regulation Advice: Procedures and An Example", *Jahrbücher für Nationalökonomie und Statistik*, Vol. 228 (2+3), 149-172.

[42] Westerhoff, F. (2001), "Speculative Behavior, Exchange Rate Volatility and Central Bank Interventions", *Central Europan Journal of Operations Research*, Vol. 9, 31-50.

[43] Westerhoff, F. (2003a), "Heterogeneous Traders and the Tobin Tax", *Journal of Evolutionary Economics*, Vol. 13, 53-70.

[44] Westerhoff, F. (2003b), "Speculative Markets and the Effectiveness of Price Limits", *Journal of Economic Dynamics and Control*, Vol. 28, 493-508.

[45] Westerhoff, F. and S. Reitz (2003), "Nonlinearities and Cyclical Behavior: The Role of Chartists and Fundamentalists", *Studies in Nonlinear Dynamics and Econometrics*, Vol. 7 (Issue 4, Article 3).

[46] Westerhoff, F. and C. Wieland (2004), "Spillover Dynamics of Central Bank Interventions", *German Economic Review*, Vol. 5, 435-450.

[47] Westerhoff, F. and R. Dieci (2006), "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*, Vol. 30, 293-322.

[48] Westerhoff, F. (2006), "Technical Analysis based on Price-Volume Signal and the Power of Trading Breaks", *International Journal of Theoretical and Applied Finance*, Vol. 9, 227-244.

[49] Westerhoff, F. (2008a), "The Use of Agent-Based Financial Market Models to Test the Effectiveness of Regulatory Policies", *Jahrbücher für Nationalökonomie und Statistik*, Vol. 228, 195-227.

[50] Westerhoff, F. (2008b), "Exchange Rate Dynamics: A Nonlinear Survey", in: Rosser, B. (ed.) *Handbook of Complexity Research*, Cheltenham.

[51] Wieland, C. and F. Westerhoff (2005), "Exchange Rate Dynamics, Central Bank Interventions and Chaos Control Methods", *Journal of Economic Behavior and Organization*, Vol. 58, 117-132.

[52] Winker, P., M. Gilli and V. Jeleskovic (2007), "An Objective Function for Simulation Based Inference on Exchange Rate Data", *Journal of Economic Interaction and Coordination*, Vol. 2, 125-145.