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Heterogeneous traders and the Tobin tax*

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Abstract. To study the effectiveness of the Tobin tax, we develop a model of heterogeneous interacting agents. Traders either speculate on the basis of technical or fundamental analysis, or abstain from the market, a decision which depends on profit considerations, as well as communication between agents. Simulations generate stylized facts such as unit roots in exchange rates, fat tails for returns, or volatility clustering. The imposition of a Tobin tax leads to a crowding out of speculators and stabilizes the dynamics. However, the decreasing impact of fundamentalists triggers misalignments if tax rates are too high.

Key words: Foreign exchange markets – Tobin tax – Technical and fundamental analysis

JEL Classification: F31, G14

1 Introduction

Since speculators cause foreign exchange markets to be excessively volatile, the flow of goods between countries and the choice of production is inefficient. Following this presumption, Tobin (1978), extending an argument of Keynes (1936), proposes the imposition of an internationally uniform tax on all currency transactions in order to discourage speculation. Advocates of the Tobin tax claim that a small proportional transaction tax of, say, half a percent does not harm international trade,

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but severely penalizes speculators engaged in short-term, high-frequency trading. Such a device would have the additional advantage of raising a substantial amount of tax revenue.

By throwing sand in the wheels of foreign exchange markets, one hopes to prevent a certain type of trader from entering the market, the goal being to exclude traders who base their investments on pseudo-signals and feedback rules. But a transaction tax does not only punish so-called chartists. Fundamentalists are traders who bet on a convergence between prices and fundamentals. Selling overpriced and buying underpriced currencies placates the dynamics. Clearly, if fundamentalists react more sensitively to a Tobin tax than chartists, foreign exchange markets may be distorted.

Unfortunately, only few dynamical models deal with the effectiveness of transaction taxes (for a general discussion see, e.g., Eichengreen et al., 1995, or Haq et al., 1996). Tornell considers a model in which investment in real capital is irreversible and dept-financed. Since a Tobin tax reduces the variance of the domestic interest rate, underinvestment diminishes. Reinhart (1991) studies a portfolio balance model in which the imposition of a tax on domestic holdings of the foreign asset produces a transitory deterioration in the trade balance which mirrors the capital account surplus as investors deplete their stocks of foreign assets. Kupiec (1996) and Ehrenstein (2002) explicitly model destabilizing speculators. While in the former contribution a transaction tax may reduce the price volatility of stocks, the level of the stock prices also declines as agents discount the future tax liability associated with stock ownership. In the latter study, a Tobin tax reduces price changes, since the profitability of speculation declines. However, the model contains neither fundamental traders nor does it allow deviations from fundamental values to play a role.

The aim of this paper is to develop a simple model which allows us to understand how a transaction tax may influence the behavior of heterogeneous agents. Our model is built on the grounds of a chartist-fundamentalist setting. Contributions by Brock and Hommes (1997, 1998), Lux (1997), Lux and Marchesi (2000) and Farmer and Joshi (2002) show that the interaction between boundedly rational agents, who rely on different predictors to forecast price movements, generates complex dynamics. These models have the potential to mimic important time series properties of financial data quite closely.

In our framework, market participants are free to engage in speculative activity. If they enter the market, they use technical and fundamental analysis to derive their orders. The market shares of the these options are updated every period. First, agents pay greater attention to those strategies that have produced profits in the recent past. Second, traders are influenced by their social environment and thus may imitate the behavior of others. Simulations reveal that our model is able to replicate stylized facts such as unit roots in exchange rates, excess volatility, fat tails for returns and volatility clustering.

The imposition of a small transaction tax crowds out both chartists and fundamentalists. Since the profitability of speculation declines, agents refrain from trading. As a consequence, exchange rates are closer to fundamentals and less volatile. But this is not the end of the story. If the tax exceeds a certain threshold, the reduction of the number of fundamentalists causes exchange rates to disconnect from fundamentals. Due to the emergence of bubbles, chartism becomes profitable from time to time and volatility rises on average.

The paper is organized as follows. Section 2 develops our model. First, we present some empirical support for the model and then we discuss the setup. After some comments on the parameter setting, we explore various time series properties of the model. In Section 3, we study the effectiveness of the Tobin tax. Section 4 offers several conclusions.

2 The model

2.1 Motivation

The foreign exchange market is the world's largest financial market. The BIS (2002) reports that the global turnover in traditional foreign exchange market segments reached an estimated daily average of US $ 1.2 trillion in April 2001. According to the BIS, the foreign exchange market is highly influenced by speculators. On the one hand, the overwhelming part of the trading volume reflects short-term transactions. For instance, operations of intra-day traders account for 75 percent of the market volume. On the other hand, only 15 percent of the trading volume is on account of non-financial customers, with international trade transactions representing merely one percent of the total.

Survey studies, such as Taylor and Allen (1992) and Menkhoff (1997), indicate that professional traders rely on rather simple trading rules when determining their orders. Trading rules belong to either the class of fundamental or technical analysis. Both concepts appear to be equally important. Most traders are familiar with both types of analysis; only a minor fraction of agents adhere permanently to one class.

Fundamental analysis is built on the premise that exchange rates converge toward their fundamentals. Fundamental trading rules suggest buying (selling) foreign currency when the exchange rate is below (above) its fundamental value (Moosa, 2000). Rules based on technical analysis derive trading signals from past price movements – their goal is to exploit regularities in the time series of prices by extracting patterns from noisy data. Trading signals are either derived by visual inspection of price charts or by applying quantitative rules (Murphy, 1999). Rules belonging to the former class include the head-and-shoulders pattern or triangles; examples of the latter group are moving averages or momentum rules. Technical trading signals are obviously much more diverse than fundamental trading signals. In total, they appear rather random.

Our model is based on such findings. Traders select between three alternatives: they may apply either technical or fundamental trading rules to determine their orders or they may abstain from the market. The decision is repeated in every period and influenced by two aspects: traders tend to prefer those rules which have been profitable in the recent past, but also observe what others do and communicate with one another. According to Shiller (1995), people tend to imitate the behavior of others (herding behavior). In our model, the evolution of the market shares of the traders' options thus rests on a direction-giving force governed by the fitness of the alternatives and a random component due to social interactions.

Foreign exchange dynamics clearly depend on the behavior of the market participants. Suppose that a large majority of traders rely on fundamental analysis. If so, then exchange rates should be close to fundamentals. However, if traders switch to technical analysis, the market becomes less stable. In this context, it seems to be interesting to ask how a Tobin tax alters the behavior of traders. The Tobin tax obviously imposes additional costs on market participants and may make otherwise successful investments unprofitable. At first sight, one would expect that traders retreat from the market and that volatility therefore declines. But note that traders are heterogeneous. What happens if the Tobin tax shifts the relation between chartists and fundamentalists in the direction of the former? Could it even be possible that the fraction of chartists rises when fundamentalists are eliminated? To answer these questions, we develop a dynamical model which may help to evaluate the effectiveness of the Tobin tax.

2.2 Setup

We consider transactions from international firms and speculators. The demand for currency is expressed in terms of market orders. A market order is a request to transact immediately at the best available price. For large market orders, the fill price is typically unknown. The price impact function (1) relates the net of all such orders at time t to the exchange rate S in t+1

$$S_{t+1} = f(S_t, ed_t), \tag{1}$$

where f (•) is an increasing function of the excess demand

$$ed_t = d_t^I + m_t^C d_t^C + m_t^F d_t^F. \tag{2}$$

The excess demand is given as the sum of the orders of the firms, d^I, the chartists, d^C, and the fundamentalists, d^F. Transactions of the latter two groups are weighted by their market shares, m^C and m^F, respectively. The weight of traders who do not enter the market is denoted by $m^O (m^C + m^F + m^O = 1)$. Combining (1) and (2) and assuming a linear relation between relative price changes and excess demand yields

$$S_{t+1} = S_t + S_t\, \alpha^M (d_t^I + m_t^C d_t^C + m_t^F d_t^F), \tag{3}$$

where α^M is a positive and constant scale factor to normalize the order size. Clearly, buying drives the price up, and selling drives it down.

The liquidity management of international firms, either due to trade or risk management operations, results in orders which are formalized as

$$d_t^I = \alpha^{I,1}(F_t - S_t)/S_t + \alpha^{I,2} dr_t^I. \tag{4}$$

The first term reflects the usual current account relationship. If the exchange rate is higher (lower) than its fundamental value F, then exports exceed (fall short of) imports. But on a day-to-day basis this relationship does not always hold. Even a medium current account imbalance may be overcompensated by random liquidity orders of firms. This effect is captured by the second term, where dr^{I} ~N(0,1). The reaction coefficients $\alpha^{I,1}$ and $\alpha^{I,2}$ are positive and constant. To make life easy, we assume that a (low) Tobin tax has no impact on the demand of firms.

The development of the fundamental exchange rate is due to the news arrival process and follows a geometric Brownian motion

$$F_t = F_{t-1} \exp \eta_t. \tag{5}$$

The news η is identically and independently distributed according to a Normal distribution with mean zero and constant variance.

Traders apply technical or fundamental analysis to determine their orders, although they are not forced to trade. The term technical analysis is a general heading for a myriad of trading strategies. Since there are probably as many methods of combining and interpreting these rules as there are chartists themselves, their orders appear largely random. Hence, we express the demand of chartists as

$$d_t^C = \alpha^C dr_t^C, \tag{6}$$

wherea^C is a positive reaction coefficient and *dr* ^{C} ~N(0,1).[1]

Fundamental analysis is built on the premise that exchange rates converge towards their fundamentals. Assuming that all agents perceive F correctly, orders of fundamentalists may be written as

$$d_t^F = \alpha^F (F_t - S_t)/S_t. \tag{7}$$

Fundamentalists take a long (short) position if the exchange rate is below (above) its fundamental value.

The development of the market shares of the traders' options is crucial to the dynamics. The weight of each alternative is defined as

$$m_t^C = m^C + (1 - m^C - m^F)\frac{i_t^C}{i_t^C + i_t^F + i_t^O}, \tag{8}$$

$$m_t^F = m^F + (1 - m^C - m^F)\frac{i_t^F}{i_t^C + i_t^F + i_t^O}, \tag{9}$$

$$m_t^O = (1 - m^C - m^F)\frac{i_t^O}{i_t^C + i_t^F + i_t^O}, \tag{10}$$

where m^C and m^F denote the minimum fractions of agents who always rely on technical or fundamental analysis, respectively. Market shares change over time depending on the popularity indices i^C, i^F and $i^O$of the traders' alternatives.

The evolution of the popularity indices is subject to two conditions: communication and success. The update takes place as follows

$$i_t^C = i_{t-1}^C + ir_t^C + g_t, \tag{11}$$

$$i_t^F = i_{t-1}^F + ir_t^F + g_t, \tag{12}$$

$$i_t^O = i_{t-1}^O + ir_t^O + g_t. \tag{13}$$

[1] One may also regard this type of agent as a noise trader.

First, the popularity of each option is adjusted by a random variable in every period, where ir^C, ir^F and ir^O are uniformly distributed within the range of $\pm c$. This update reflects the phenomenon that market participants regularly communicate with one another about their trading activity. As a result, traders may become convinced that one rule is superior to another. The exchange of information can also be interpreted as herding behavior. Agents simply adopt the behavior of others.

Second, traders evaluate the profitability of their strategies every K period. If a rule has produced any profit $(P_t > 0)$, its popularity grows by g. In the opposite case, it shrinks by g. Since $g_t = 0$ for $t \notin \{K, 2K, 3K...\}$ or $P_t = 0$, the profitability update may be expressed as

$$g_t = \begin{cases} +g, & t \in \{K, 2K, 3K, ...\} \wedge P_t > 0 \\ -g, & t \in \{K, 2K, 3K, ...\} \wedge P_t < 0 \\ 0, & t \notin \{K, 2K, 3K, ...\} \vee P_t = 0 \end{cases} . \tag{14}$$

The evolution of the indices is restricted to some positive interval $i^{\min} < i^C, i^F, i^O < i^{\max}$.

The profitability of technical and fundamental analysis is computed as

$$P_t^C = S_t \sum_{l=1}^{L} d_{t-l}^C - \sum_{l=1}^{L} S_{t-l+1} d_{t-l}^C - tax \sum_{l=1}^{L} \left| S_{t-l+1} d_{t-l}^C \right|, \tag{15}$$

$$P_t^F = S_t \sum_{l=1}^{L} d_{t-l}^F - \sum_{l=1}^{L} S_{t-l+1} d_{t-l}^F - tax \sum_{l=1}^{L} \left| S_{t-l+1} d_{t-l}^F \right|. \tag{16}$$

The agents use a time window of L periods. The first term stands for the final revenue from clearing the position, the second term for the permanent revenue from building up the position, and the third term for the payment due to the Tobin tax.

The price evolution equation is obtained by combining (3)–(16). Since the solution is a high-dimensional nonlinear stochastic difference equation, it precludes closed analysis. We therefore simulate the dynamics to demonstrate that the underlying structure gives rise to realistic fluctuations.

2.3 Calibration

Table 1 displays the basic parameter setting we use for the simulations. Since our model is relatively simple, the replication of the dynamics should be straightforward. Adjusting the coefficients reveals that the time series properties of our model are rather robust under parameter variations. Unfortunately, most parameters cannot be observed empirically. Survey studies such as Taylor and Allen (1992) suggest that around 10 percent of market participants stick permanently to one type of trading rule, hence $m^C = m^F = 0.1$. Furthermore, we assume that agents compare the profitability of the trading strategies every 60 periods. Since our model is calibrated to daily exchange rate fluctuations, $K = 60$ is equivalent to one quarter.

Table 1. Basic parameter setting

α^M=0.025	$\alpha^{I,1}$=0.01	$\alpha^{I,2}$=0.1	α^C=1
α^F =1	m^C =0.1	m^F =0.1	K =60
g =25	c =5	$i^{\min}$ =0	tax =0
L =60	σ^η =0.0025	$i^{\max}$ =75	F_1 =100
S_t=100,$t\in\{1,..K\}$	i^C_t=37.5,$t\in\{1,...K\}$	i^F_t=37.5,$t\in\{1,...K\}$	i^O_t=37.5,$t\in\{1,...L\}$

Profits are computed with a time window of $L = 60$ periods. If a rule is profitable (unprofitable), its index rises (declines) by $g = 25$. The impact of communication is uniformly distributed over the interval ± 5. The popularity indices are bounded within 0–75. With the help of the reaction coefficients, the volatility of the model is calibrated to values observed empirically. Next, we explore the dynamics without a Tobin tax ($tax = 0$).

2.4 Simulation

This section demonstrates that the model is able to produce: (1) unit roots in exchange rates, (2) lasting bubbles, (3) excess volatility, (4) fat tails for returns, and (5) volatility clustering. Properties (1), (4) and (5) may be regarded as universal features of financial markets. Bubbles and excess volatility are, however, difficult to quantify empirically. Surveys on exchange rate dynamics are provided, for instance, by Guillaume et al. (1997) and Lux and Ausloos (2002).

Figure 1 gives an overview of the dynamics for the first T= $1,000$ periods. The solid line in the top panel represents the exchange rate and the dashed line shows its fundamental value. In the second panel, relative changes in exchange rates are plotted. The third panel shows the evolution of the market shares of the traders' options, where black, white and gray stand for chartism, no-trading and fundamentalism, respectively.

What drives the exchange rates? Note that there is an enduring competition between the three strategies. None of the options completely eliminated nor does one alternative suppress the others. Due to this fact, the dynamics evolve in quite a complex manner. The general picture one obtains is that exchange rates circle erratically around their fundamental values, whereby the degree of misalignments and fluctuations is time-dependent.

Although market shares vary permanently, single strategies become dominant in the short run. Let us focus on three distinct periods. Around $t = 400$, the majority of traders rely on fundamental analysis. During this time, volatility and distortion are moderate. Between $t = 500 - 700$, chartism is powerful and destabilizes the market. Exchange rates fluctuate wildly and may separate from fundamentals. Shortly before period 800, agents start to retreat from trading. Due to the absence of fundamentalism, exchange rates fluctuate at some distance parallel to fundamental values. A medium impact of chartists results in medium exchange rate movements.

One stylized fact of the empirical literature is that exchange rates display unit roots (Goodhart et al., 1993). The augmented Dickey-Fuller unit root testing procedure tests the null hypothesis that any shock to exchange rates is permanent against

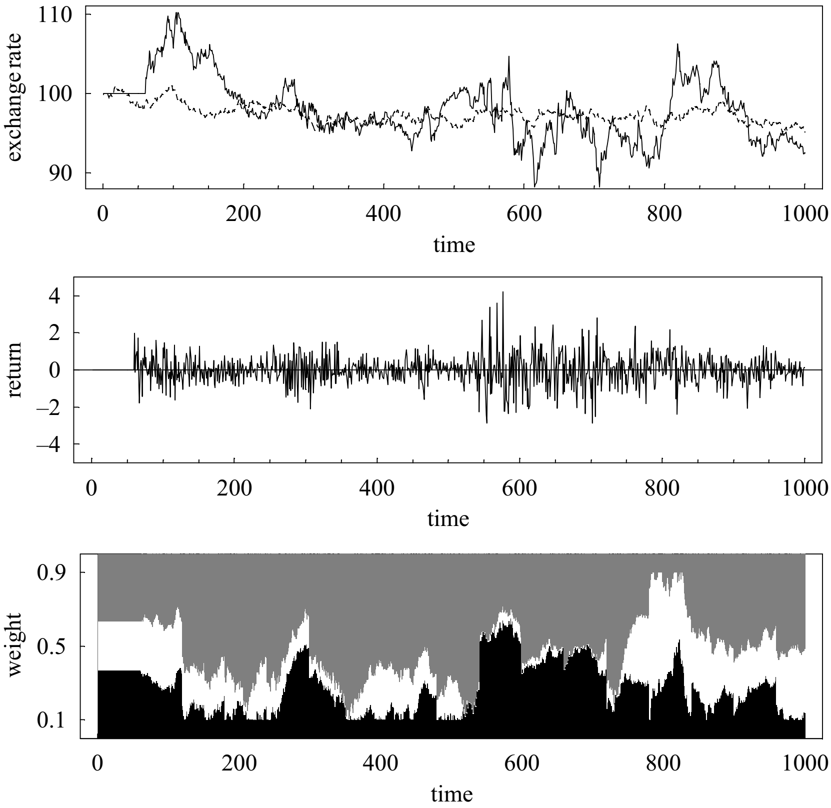

Fig. 1. Short-term fluctuations. The first panel shows the exchange rate (*solid line*) and its funda-mental value (*dashed line*), the second panel the returns, and the third panel the evolution of the weights of the trading options (m^C = black, m^O = white, m^F = gray). Parameters as in Table 1, T= $1,000$

the alternative hypothesis that a shock is only temporary. Using, for instance, a four-lag specification without intercept delivers

$$\Delta S_t = a_0 S_{t-1} + a_1 \Delta S_{t-1} + a_2 \Delta S_{t-2} + a_3 \Delta S_{t-3} + a_4 \Delta S_{t-4}, \tag{17}$$

where Δ denotes the first difference. The null hypothesis of a unit root is rejected if a_0 is significant. Table 2 compares estimation results for DEM/USD, DEM/JPY and simulated exchange rates. Since the empirical t-values exceed the critical t-values, it is not possible to reject the hypothesis of the existence of a unit root. This result is often interpreted as evidence for a random walk behavior of exchange rates.

Figure 2 and Table 3 illustrate some other long-term properties of the model (T= $10,000$). Let us first define returns as relative changes in exchange rates

$$r_t = (S_t - S_{t-1})/S_{t-1}, \tag{18}$$

and volatility as average absolute relative changes in exchange rates

$$\mathrm{V} = \frac{100}{T-1} \sum_{t=2}^{T} |(S_t - S_{t-1})/S_{t-1}|. \tag{19}$$

Table 2. Unit roots. Daily DEM/USD and DEM/JPY exchange rates from 1974–1998, T= 6, 264; the simulation is based on the parameter setting of Table 1, T= 10, 000. Empirical t-values are given in paren-theses, critical t-values for a_0 are -1.95 and -2.58 at the 5 and 1 percent significance level

Time series	a_0	a_1	a_2	a_3	a_4
DEM/USD	−0.0001	−0.0314	−0.0051	0.0343	−0.0033
	(−1.432)	(−2.484)	(−0.407)	(2.716)	(−0.261)
DEM/JPY	0.0000	0.0156	0.0157	−0.0216	−0.0080
	(0.577)	(1.232)	(1.243)	(−1.710)	(−0.633)
Simulation	−0.0001	−0.0286	−0.0376	−0.0224	−0.0066
	(−1.015)	(−2.262)	(−2.977)	(−1.769)	(−0.524)

Table 3. Some stylized facts. Daily DEM/USD and DEM/JPY returns from 1974–1998, T= 6, 263; the simulation is based on the parameter setting of Table 1, T= 10, 000

Time series	r_{min}	r_{max}	V	D	Tail index	ARCH	GARCH
DEM/USD	−5.75	4.95	0.50	–	3.58	0.11	0.88
DEM/JPY	−3.84	8.94	0.44	–	3.69	0.11	0.88
Simulation	−5.06	5.12	0.60	3.96	3.56	0.09	0.90

Similarly, distortions are measured as average absolute relative deviations between exchange rates and fundamentals

$$\mathrm{D} = \frac{100}{T} \sum_{t=1}^{T} |(S_t - F_t)/F_t|. \tag{20}$$

Now, the top panel of Figure 2 shows relative deviations of exchange rates from fundamentals. Although the misalignments do not exceed the four percent level on average (D=3.96), some stronger and durable bubbles emerge. Exchange rates may deviate up to 20 percent from fundamentals.

The second panel displays the evolution of returns. Extreme returns are around five percent. The volatility for our simulation run is computed as V= 0.6 and is comparable to DEM/USD returns (V= 0.5) and DEM/JPY returns (V= 0.44). Bartolini and Giorgianni (2001) support the notion that major currencies have been excessively volatile throughout the post-Bretton Woods era. For them, such volatility estimates are too high to be justified by fundamental shocks. Our approach allows the precise calculation of excess volatility. Changes in exchange rates are roughly three times larger than in fundamentals.

The left-hand central panel compares the distributions of simulated returns (dotted line) with normally distributed returns (solid line). The probability density function of simulated returns obviously reveals fat tails. Relative to a Normal distribution, one finds a stronger concentration around the mean, thinner shoulders and more probability mass in the tails of the distribution.

Fat tails are increasingly quantified by the tail index (Lux and Ausloos, 2002). Hill (1975) provides an estimator which is easy to compute. The sample elements are placed in descending order: $X_T > X_{T-1} > ... > X_{T-k} > ... > X_1$, with k being the number of observations located in the tail. The Hill tail index estimator

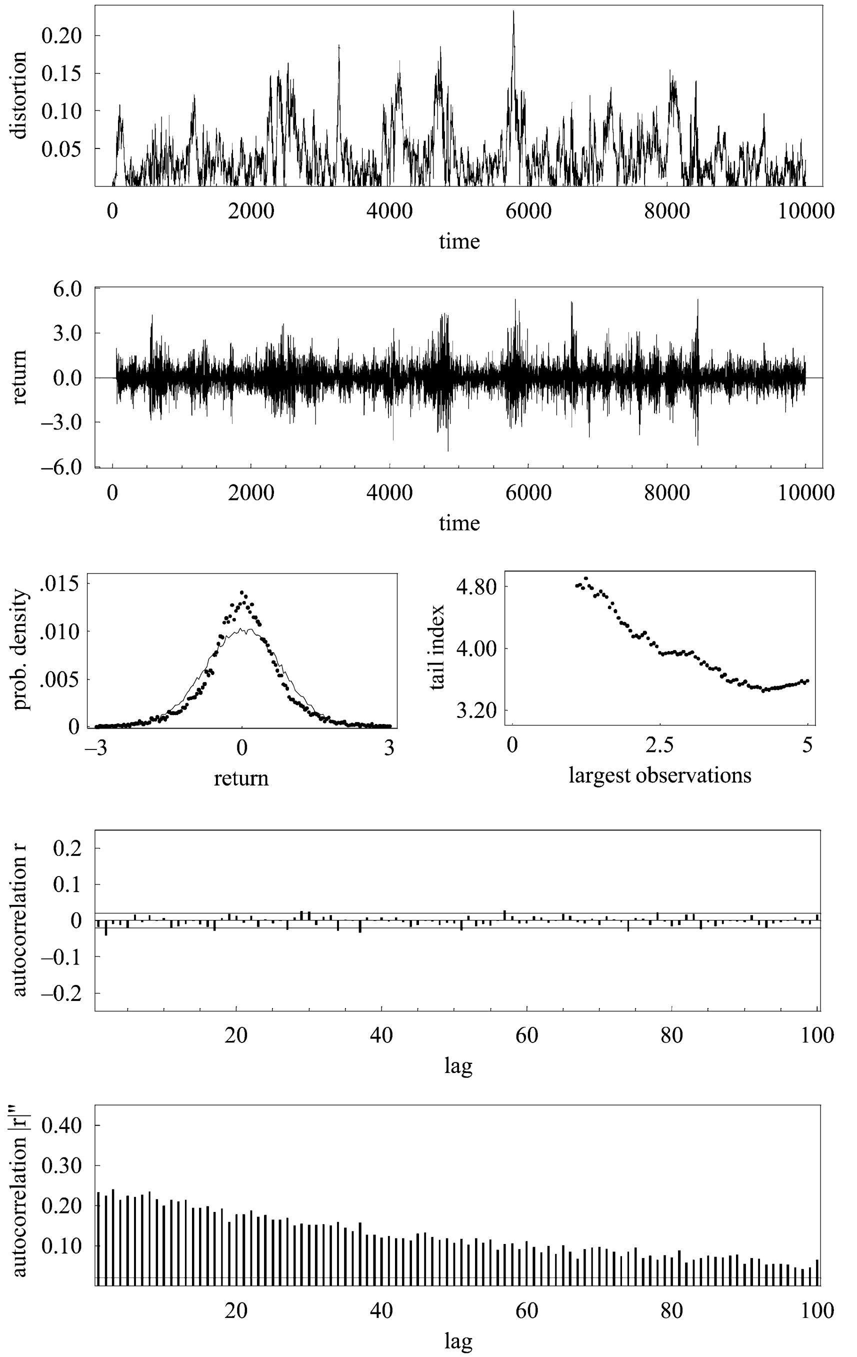

Fig. 2. Long-term properties. The first two panels show relative deviations between the exchange rate and its fundamental value and the return process, the left-hand central panel the probability density function of returns (*dotted line* = simulated returns, *solid line* = normally distributed returns), the right-hand central panel the tail index depending on the largest observations (in percent), and the final two panels the autocorrelation functions of raw returns and absolute returns (with 95 percent confidence bands). Parameters as in Table 1, T= $10,000$

is derived as

$$a = \left(\frac{1}{k} \sum_{i=1}^{k} Log\, X_{T-i+1} - Log\, X_{T-k} \right)^{-1}. \tag{21}$$

Note that the lower a, the fatter the tails. The estimate depends on an appropriate choice of the tail region. The right-hand central panel contains estimates for tail fractions between 0 and 5 percent. Since a is equal to 3.56 at the 5 percent level, it corresponds well with estimates obtained for major currencies (compare Table 3).

The last two panels display the autocorrelation functions of raw returns and absolute returns. Exchange rates tend to show almost no autocorrelation in raw returns (Guillaume et al., 1997). This is also true for our simulation. For almost all lags, the autocorrelation of raw returns is not significant. This is rather surprising: although exchange rates circle around fundamental values in the long run, no evidence of mean reversion is found in the autocorrelation function of raw returns.

A robust stylized fact observed in foreign exchange markets is volatility clustering (Mandelbrot, 1963). The second panel of Figure 2 reveals that periods of low volatility alternate with periods of high volatility. Indeed, the autocorrelation functions for absolute returns, displayed in the third panel, is highly significant.

Volatility clustering is also captured by the famous GARCH class of models. A GARCH (1,1) specification, often used in financial time series analysis, is given by

$$r_t = c_1 + \varepsilon_t, \tag{22}$$

$$\sigma_t^2 = c_2 + \alpha\, \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2. \tag{23}$$

The first equation gives the conditional mean as a function of a constant c_1 and an error term ε. In the second equation, the conditional variance is a function of a constant c_2, news about the volatility from the previous period (the ARCH term), and the last period's forecast variance (the GARCH term). Since the sum of the ARCH and GARCH coefficients is close to one (α = 0.09, β = 0.90), volatility shocks are quite persistent.

So far we have illustrated the dynamics for a single time series. Table 4, based on a Monte Carlo analysis with 10,000 simulation runs, contains various quantiles for the main statistics. As we can see, the dynamic properties of the model are very robust. For instance, the lower and upper quartile of the volatility (distortion) are given as 0.550 and 0.590 (3.956 and 4.701), respectively. The tail index is located between 3.464 and 4.182 in 90 percent of the cases. There exists almost no autocorrelation in raw returns, but strong autocorrelation in absolute returns.[2] Furthermore, the unit root hypothesis is only rejected in 2 out of 10,000 cases.

To summarize, our empirically motivated model of interacting heterogeneous speculators is able to replicate some important time series properties of foreign

[2] This joint feature is difficult to achieve in most chartist-fundamentalist models. Within our model, the demand of fundamentalists and international firms exercises some mean reversion pressure. However, the random orders of chartists destroys almost all structure in raw returns. Volatility clustering with significant autocorrelation coefficients up to 100 lags is triggered by the way how the market shares of the traders options vary. Clearly, if the market shares change too rapidly (e.g. for low values of K combined with high values of g), volatility clustering weakens.

Table 4. Some quantiles of the stylized facts. Calculations are based on 10,000 simulation runs with 10,000 observations each. a_r^j and $a_{|r|}^j$ denote the j-th autocorrelation coefficient of raw returns and absolute returns, respectively

Quantile	r_{min}	r_{max}	V	D	Tail index
0.05	−6.704	3.830	0.524	3.543	3.464
0.25	−5.592	4.350	0.550	3.956	3.667
0.50	−5.023	4.786	0.570	4.303	3.813
0.75	−4.545	5.316	0.590	4.701	3.964
0.95	−3.972	6.268	0.620	5.383	4.182
Quantile	a_r^1	a_r^2	a_r^3	a_r^4	a_r^5
0.05	−0.027	−0.026	−0.027	−0.025	−0.026
0.25	−0.013	−0.013	−0.013	−0.012	−0.013
0.50	−0.004	−0.003	−0.004	−0.003	−0.004
0.75	0.005	0.006	0.005	0.006	0.005
0.95	0.019	0.020	0.018	0.019	0.018
Quantile	$a_{\|r\|}^1$	$a_{\|r\|}^2$	$a_{\|r\|}^3$	$a_{\|r\|}^4$	$a_{\|r\|}^5$
0.05	0.179	0.175	0.171	0.167	0.163
0.25	0.200	0.196	0.192	0.188	0.184
0.50	0.216	0.211	0.207	0.203	0.199
0.75	0.230	0.226	0.221	0.217	0.213
0.95	0.252	0.248	0.244	0.239	0.235

exchange markets. We will now continue with some laboratory experiments to test the effectiveness of the Tobin tax. Such an approach has the advantage of controlling for random shocks and allowing for the more precise measurement of volatility and distortion.

3 The effectiveness of the Tobin tax

Figure 3 presents a simulation in which traders face a Tobin tax of 1.3 percent on each transaction. Figure 3 can directly be compared with Figure 1 because it is based on the same seed of random variables. What are the differences? Simple visual inspection suggests that traders tend to retreat from the market. In numerical terms, the average value of m^0 increases from 20.8 percent to 27.4 percent (T = 1,000). Furthermore, the market seems to be less volatile. The largest returns are below 3 percent in the tax scenario, whereas they reached up to 5 percent in the no-tax case.

Overall, changes in market shares are quite intricate. To gain a better understanding of what is occurring in the market, let us look more closely on two subsamples. Relative to the no-tax scenario, fundamentalism is less popular under taxation be-

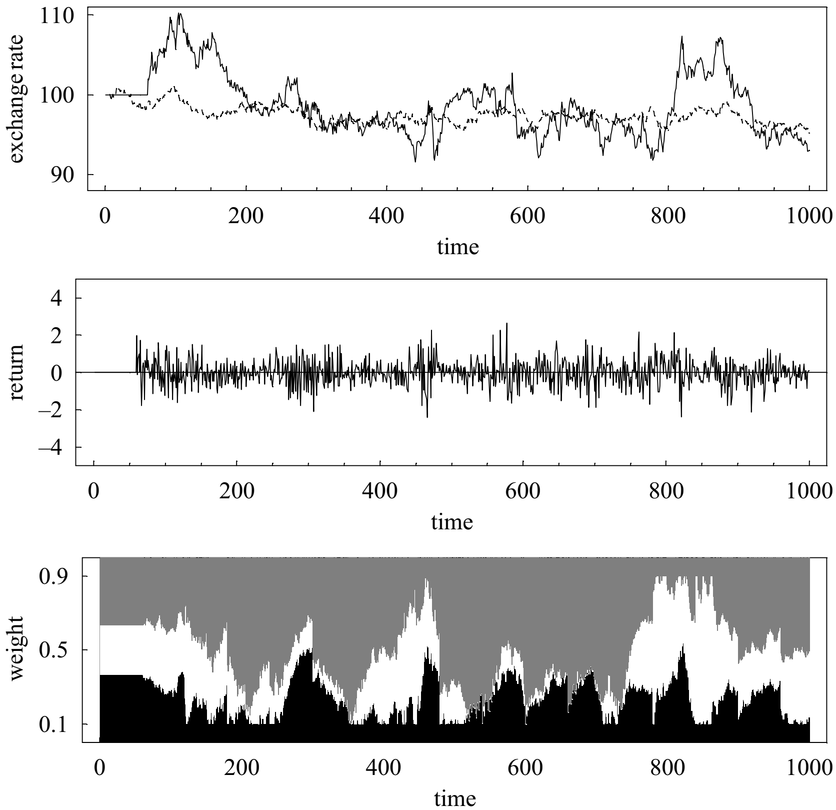

Fig. 3. The Tobin tax and evolutionary pressure. The first panel shows the exchange rate (*solid line*) and its fundamental value (*dashed line*), the second panel the returns, and the third panel the evolution of the weights of the trading options (m^C = black, m^O = white, m^F = gray). Parameters as in Table 1, but $tax = 1.3$ percent, T= $1,000$

tween $t = 400 - 500$. As a result, exchange rates deviate more strongly from fundamentals. Chartism benefits from the low popularity of fundamentalism: its market share increases for a short while, which in turn leads to higher volatility. In contrast, around period 600, the weight of fundamentalists rises at the expense of the weight of chartists. Although traders have to pay some transaction taxes, almost all of them prefer trading. Compared to the no-tax scenario, volatility is relatively moderate.

However, to evaluate the effectiveness of the Tobin tax a more general kind of analysis is needed. The solid lines in the first two panels of Figure 4 show how volatility and distortion respond to a gradual rise in the tax rate. The tax rate is increased in 50 steps from 0 to 5 percent. For each tax rate, V and D are calculated for T = 20,000. All time series are generated by using the parameter setting of Table 1. The estimates are plotted for 5 different seeds of random variables. The dotted lines indicate averages. The bottom panel shows the impact of the tax on the market

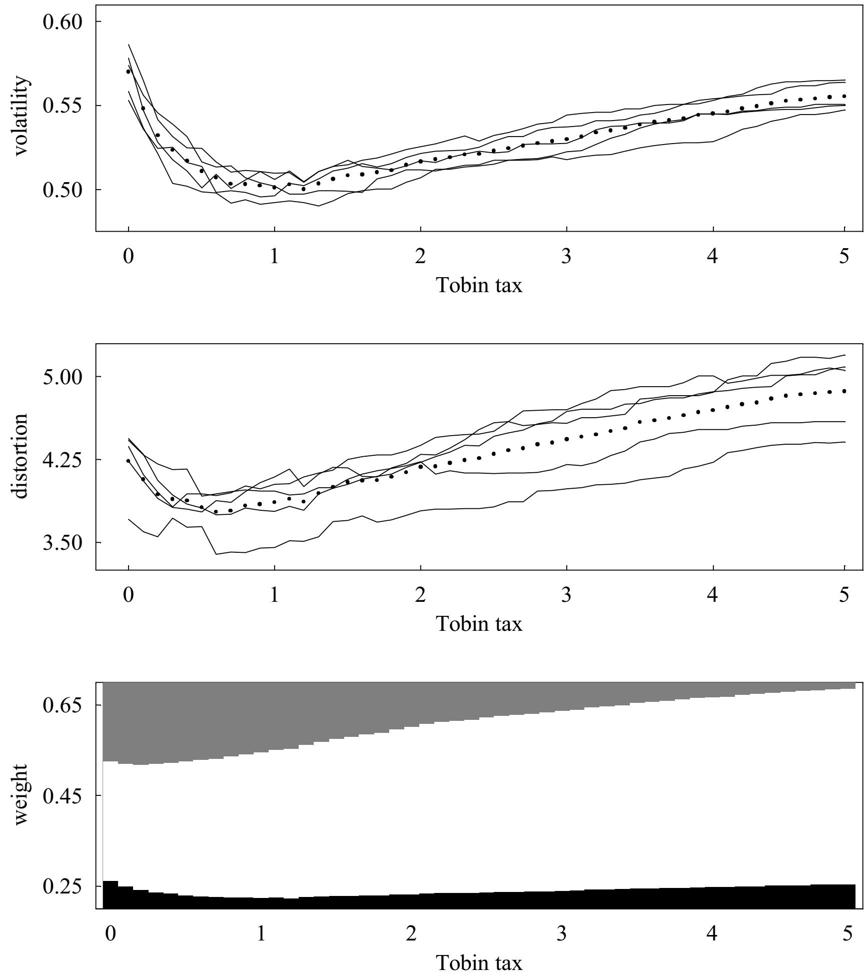

Fig. 4. Tobin tax and crowding out. The solid lines in the first two panels show volatility and distortion, respectively. Parameters as in Table 1, but tax rates are increased in 50 steps from 0 to 5 percent, T$=20,000$, 5 different seeds of random variables, the *dotted lines* indicate averages. The bottom panel displays the average weights of the trading options ($m^C=$ black, $m^O=$ white, $m^F=$ gray)

shares, where black, white and gray areas indicate average values of m^C, m^O and m^F, respectively.

Our simulation supports the taxation of currency transactions. The Tobin tax has the potential to stabilize foreign exchange markets. Volatility and distortion decline roughly between 10 and 15 percent. As a byproduct, the tax generates revenue. However, if the tax rate is set too high, it has no impact on exchange rate fluctuations, but instead worsens misalignments.

As we may see in Figure 4, a low tax rate first crowds out chartism. Due to the reduction of excess demand, volatility and distortion shrink. At around *tax* = 0.5, fundamentalists also start to leave the market.[3] On the one hand, this adds to the dampening of exchange rate movements, since the order size further declines. But on the other hand, exchange rates are less attracted towards their fundamentals.

This is an important observation. If the mean-reverting influence of fundamental analysis declines, the random nature of technical analysis produces less systematic errors. In addition, technical analysis is more likely to be self-fulfilling. Suppose that technical trading rules generate a series of buy signals at random. If these positions are not countered by fundamental trading rules, a bubble emerges during which technical analysis is highly profitable. In fact, the weight of chartism starts to grow slightly for $tax > 1$. Although an increasing number of agents stop trading, it is the wrong type of trader who vanishes.

Finally, we try to assess the robustness of our results. Figure 5 compares the impact of Tobin taxes on the dynamics for different parameter combinations. V and D are computed as in the case of the dotted lines of Figure 4. We use the parameter setting of Table 1 but vary $K = L$ and g as indicated. We must keep in mind that the update of market shares depends on how often traders evaluate the fitness of their options and by which amount they adjust the popularity indices. If agents pay more attention to the fitness of the rules, this implicitly decreases their sensitivity to social interactions. Figure 5 indicates that our results are relatively stable. The general shape of the derived functions does not alter under parameter variation. In all eight cases, V and D first decline due to taxation but then rise again.

Due to the large number of technical trading rules, the orders of chartists are assumed to be random. However, this may not always be the case. For instance, during a bubble period, chart analysis tends to predict price trends. In such times, the demand of chartists may better be expressed as

$$d_t^C = \alpha^C dr_t^C + \alpha^{C,1}(S_t - S_{t-1})/S_{t-1}, \tag{24}$$

where the first term indicates random signals as in (6) and the second term captures trend extrapolation ($a^{C,1} > 0$). Figure 6 reveals that the non-monotonic relationship between the Tobin tax and volatility and distortion is not affected by positive feedback trading (computation as in Fig. 5; solid line: $a^{C,1} = 0$, triangles $a^{C,1} = 10$, rectangles $a^{C,1} = 20$ and circles $a^{C,1} = 30$). However, the stronger the extrapolation term, the higher volatility and distortion.

To summarize, the Tobin tax is able to placate foreign exchange dynamics. However, at no tax rate, excess volatility and distortion are completely eliminated. Since the optimal tax rate is unknown, it may even be the case that policy makers set the tax rate too high and thus destabilize the market.[4]

4 Conclusions

Both theoretical and empirical evidence suggest that foreign exchange markets are excessively volatile. Following the literature, we develop a model of interacting

[3] Note that the lower the distance between exchange rates and fundamentals, the lower the profit potential of fundamental analysis.

[4] In real markets traders face (small) transaction fees. It could be possible that the transaction fees are close or even higher than the optimal tax rate. Then, a Tobin tax would always decrease stability.

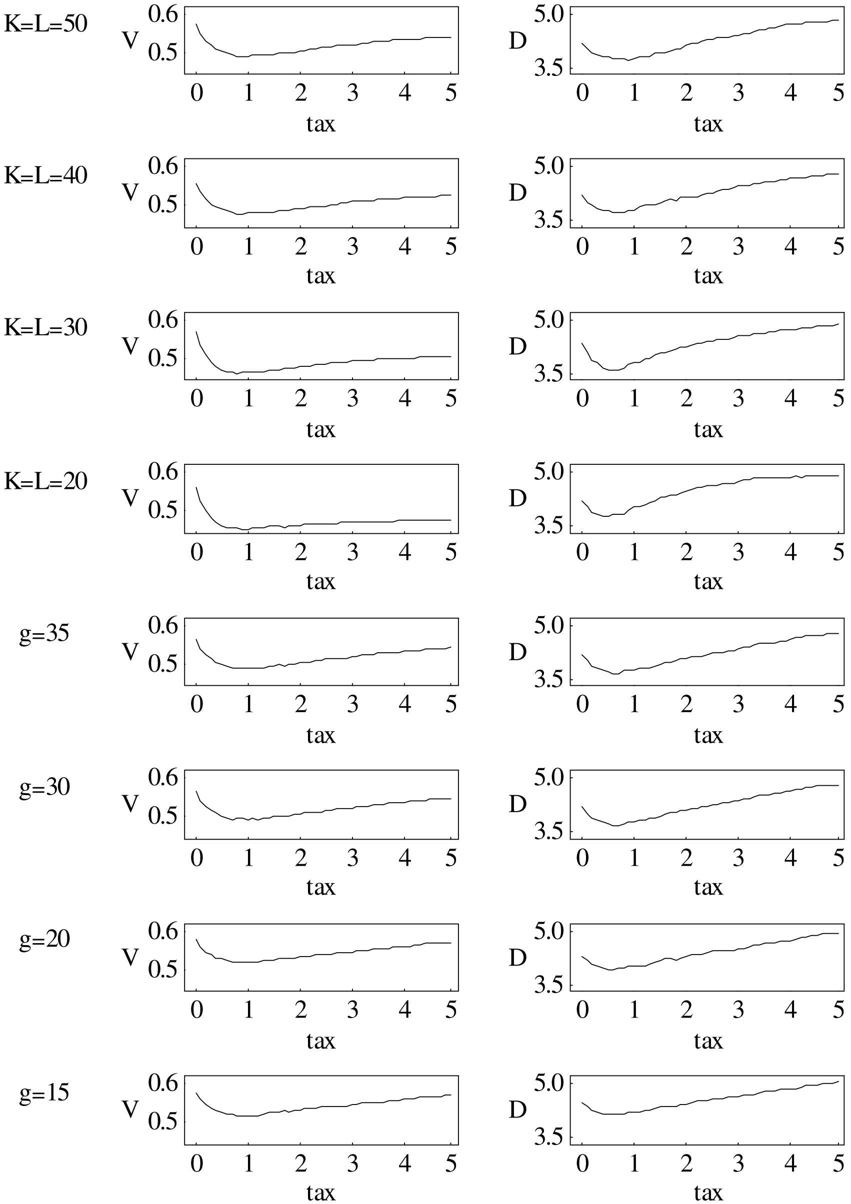

Fig. 5. The effectiveness of the Tobin tax. Volatility and distortion are plotted for rising tax rates (average values for different seeds of random variables, calculated in the same way as the dotted lines in Fig. 4). Parameters as in Table 1, but K, L, g and tax as indicated

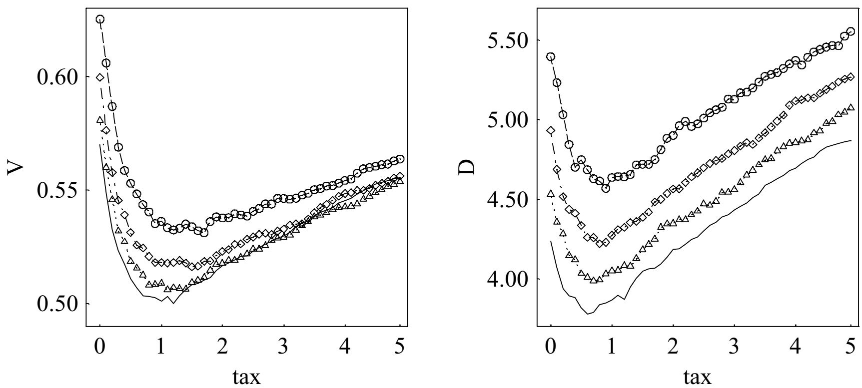

Fig. 6. The Tobin tax and positive feedback trading. Simulation design as in Figure 5; *solid line* $\alpha^{C,1} = 0$, triangles $\alpha^{C,1} = 10$, rectangles $\alpha^{C,1} = 20$, circles $\alpha^{C,1} = 30$

heterogeneous agents to explore whether a Tobin tax is able to calm the dynamics. Traders who enter the market select between technical and fundamental analysis to determine their orders. Traders base their actions on profit considerations, but are also influenced by their social environment. The interaction between market participants causes complex exchange rate fluctuations. The time series properties of our model are similar to those observed for major currencies.

Using our approach as a laboratory, we find that the Tobin tax generally has the potential to reduce volatility and distortions. By imposing a small transaction tax, the profitability of trading declines and speculators leave the market. But note that taxation affects all types of traders. Clearly, a reduction of fundamentalism always goes hand in hand with an increase in misalignments. If the tax rate exceeds a critical value, deviations of exchange rates from fundamentals start to rise. It is then the emergence of bubbles that makes destabilizing chartism profitable again.

The study of models with heterogeneous interacting agents allows exciting insights into the working of financial markets. In this sense, the chartist-fundamentalist approach offers also a new and powerful tool to evaluate certain policy measures. The results presented in this paper are preliminary, and much more work is needed. For instance, one should test the effectiveness of the Tobin tax within other models, too. We hope that our paper stimulates research in this direction.

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