Tobin Taxes and Dynamics of Interacting Financial Markets

Structured Abstract:
Purpose – The paper aims at developing a behavioral agent-based model for interacting financial markets. Additionally, the effect of imposing Tobin taxes on market dynamics is explored.
Design/methodology/approach – Agent-based approach is followed to capture the highly complex, dynamic nature of financial markets. The model represents the interaction between two different financial markets located in two countries. The artificial markets are populated with heterogeneous, boundedly rational agents. There are two types of agents populating the markets; market makers and traders. Each time step, traders decide on (i) which market to participate in, (ii) which trading strategy to follow. Traders can follow technical trading strategy, fundamental trading strategy, or abstain from trading. The time-varying market share of each trading strategy depends on current and past performance of this strategy. However, technical traders are loss averse, where losses are perceived twice the equivalent gains. Market makers settle asset prices according to the net submitted orders.
Findings - The proposed framework can replicate important stylized facts observed empirically such as, bubbles and crashes, excess volatility, clustered volatility, power-law tails, persistent autocorrelation in absolute returns, and fractal structure.
Practical implications - Artificial models linking micro to macro behavior facilitate exploring the effect of different fiscal and monetary policies. The results of imposing Tobin taxes indicate that a small levy may raise government revenues without causing market distortion or instability.
Originality/value – this research proposes a novel approach to explore the effect of loss aversion on the decision-making process in interacting financial markets framework.

Keywords – Agent-based model, loss aversion, fractal structure, simulation analysis

Article Classification – Research paper

1. Introduction

Tobin (1978) argues that imposing small, uniform taxes on all financial transactions would penalize short-term speculations and, hence, stabilize the financial market. Many European Union countries impose taxes on financial transactions. However, introducing financial transaction taxes in other financial markets is still under debate. Proponents believe that a levy of financial transaction taxes would provide sizeable revenues to governments. On the other hand, contrarians argue that introducing transaction taxes to financial markets would reduce market liquidity and a higher price volatility would be ensued. Additionally, the growing role of electronic brokering would increase tax evasion possibilities. This results in reducing the Tobin tax's ability to yield revenues,

Hesitation of imposing a levy could be due to the unexpected results of market crashes or instability. Collateral effects can be avoided by exploring the impact of regulatory policies on the dynamics of artificial financial markets. The effect of imposing Tobin taxes on the dynamics of artificial financial markets has been studied in many researches [c.f. Westerhoff and Dieci (2006), Westerhoff (2008), and Stanek and Kukacka (2017)]. However, none of these researches have considered the effect of behavioral biases on trader's decision-making process. Few efforts have been spent to introduce behavioral biases to agent-based models [c.f. Takahashi & Terano (2003), Lovric, et al. (2010), Li, et al. (2014), Selim, et al. (2015), Ezzat (2016), and Feldman & Lepori (2016)]. Nevertheless, these models are not designed to explore the dynamics of interacting financial markets. Studying interaction between international financial markets is of crucial importance specially after the recent global financial crisis [c.f. Westerhoff and Dieci (2006), and Schmitt and Westerhoff (2014)]. This research introduces loss-aversion behavior to the framework of interacting financial markets proposed by Westerhoff and Dieci (2006).

The aforementioned models can replicate some important stylized facts, which are common statistical features observed in most financial markets. Significant stylized facts are usually formulated in terms of qualitative and quantitative properties such as, price bubbles and market crashes, random-walk prices, clustered volatility, excess volatility, and long memory [c.f. Mandelbrot (1963), Fama (1970), Guillaume, et al. (1997), Cont (2001), Cont (2005), and Haas & Bigorsch (2011)].

A simple behavioral agent-based model of two interacting financial markets is developed. The model is structured as follows. The markets are populated with two types of agents; market makers, and traders. At each time step, traders decide either to trade or to stay inactive. Active traders follow technical or fundamental trading strategy as suggested by previous surveys [c.f. Taylor and Allen (1992), Menkhoff (1997), and Frankel and Froot (1987a; 1987b; 1990)] and laboratory experiments [c.f. Hommes (2011)]. Technical trading aims at exploiting price trends. Conversely, fundamental trading seeks to take advantage of mean reversion. Traders can participate in one market at a time. The attractiveness of a trading strategy is determined by the performance of this strategy in most recent past, which demonstrates a learning behavior. Trading-strategy weights are computed using the discrete-choice model proposed by Manski and McFadden (1981). However, traders following technical analysis are loss averse, where losses loom larger than equivalent gains. Accordingly, market shares of technical trading are expressed in terms of a piecewise linear function proposed by the prospect theory [c.f. Kahneman and Tversky (1979, 1984, 1991, 1992)]. There is a market maker located in each market. Market makers set asset prices according to the net submitted orders. For this purpose, a linear impact function proposed by Farmer & Joshi (2002) is followed. Agents interact indirectly through their influence on price adjustment. This affects the attractiveness of trading rules which turns to affect the belief adaptation process.

By simulation, results show that the developed model can generate financial time series that exhibit important stylized facts observed empirically such as, bubbles and crashes, volatility clustering, power-law tails, long memory, and fractal structures. Thereafter, the proposed model serves as a test-bed for policy makers to investigate the effect of levying taxes on financial transaction. The impact of levying financial transaction taxes on the market dynamics is extensively investigated.

The rest of the paper is organized as follows. In Section 2, the proposed agent-based financial market model is presented. Asset pricing dynamics is investigated in Section 3. Furthermore, the results of extensive Monte Carlo simulation are displayed. In Section 4, the effect of imposing transaction taxes on market dynamics is investigated. The last section concludes the paper.

2. The Model

There are two different stock markets, market *X* and market *Z*, located in two countries. It is assumed that the countries either share the same currency or have agreed upon a fixed exchange rate. For simplicity, the two stock markets are assumed to be symmetric. Thereby, traders have no preference for one market over the other. There are two types of agents; market makers and traders. In each time step $t,\ t = 0,1, \dots ,\ T$, each trader decides either to submit orders or abstain from the market. If a trader chooses to submit an order, she/he can submit her/his order either to market *X* or market *Z*. In addition, the trader can follow either technical or fundamental trading rule. Therefore, if the trader decides to submit an order; she/he would choose between four trading alternatives (two different stock markets and two different trading rules).

Market makers settle asset prices following a log-linear price impact function suggested by Former and Joshi (2002). This function measures the relation between the orders quantity (demand/supply) and the price of the asset. Thus, asset log price in period *t*+1 for markets *X* and *Z*, can be given by

$$p_{t+1}^X = p_t^X + a\left(w_t^{Xc} D_t^{Xc} + w_t^{Xf} D_t^{Xf}\right) + \alpha_t^X, \tag{1}$$

and

$$p_{t+1}^Z = p_t^Z + a\left(w_t^{Zc} D_t^{Zc} + w_t^{Zf} D_t^{Zf}\right) + \alpha_t^Z, \tag{2}$$

where p_t^X and p_t^Z are the log prices at time *t* in markets *X* and *Z*, respectively, a is a positive price settlement parameter, D_t^{Xc} and D_t^{Zc} are the orders submitted at time *t* by chartists to markets *X* and *Z*, respectively, D_t^{Xf} and D_t^{Zf} are the orders submitted at time *t* by fundamentalists to markets *X* and *Z*, respectively, w_t^{Xc} and w_t^{Xf} are the weights of technical and fundamental strategy, respectively, in market *X* at time *t*, and w_t^{Zc} and w_t^{Zf} are the shares of chartists and fundamentalists, respectively, in market *Z* at time *t*. To make the assumptions close to the real markets, noise terms α_t^X and α_t^Z are added to catch any random factors affecting the price settlement process in markets *X* and *Z*, respectively. It is assumed that, α_t^X and α_t^Z , $t = 1, 2, \dots, T$ are IID normally distributed random variables with mean zero and constant standard deviations σ_α^X and σ_α^Z, respectively.

Chartists follow technical analysis to exploit price changes (Murphy, 1999). Technical trading orders submitted to markets *X* and *Z*, respectively, at time *t* can be written as

$$D_t^{Xc} = b(p_t^X - p_{t-1}^X) + \beta_t^X, \tag{3}$$

and

$$D_t^{Zc} = b(p_t^Z - p_{t-1}^Z) + \beta_t^Z, \tag{4}$$

where *b* is a positive reaction parameter (also called extrapolating parameter) that captures the sensitivity of chartists to price changes. The first term at the right-hand side of (3) and (4) represents the difference between current and last price, which indicates the exploitation of price changes. The second term captures additional random orders of technical trading rules. β_t^X and $\beta_t^Z, t = 1, 2, \dots, T$ are IID normally distributed random variables with mean zero and constant standard deviation σ_β^X and σ_β^Z, respectively.

Fundamental analysis assumes that prices will revert to their fundamentals in the short run (Graham & Dodd, 2009). Orders submitted by fundamentalists to markets *X* and *Z*, respectively, at time *t* can be descried by

$$D_t^{Xf} = c(f_t^X - p_t^X) + \gamma_t^X, \tag{5}$$

and

$$D_t^{Zf} = c(f_t^Z - p_t^Z) + \gamma_t^Z, \tag{6}$$

where c is a reaction parameter (also called a reverting parameter) that captures the sensitivity of fundamentalists to price mean reversion. f_t^X and f_t^Z are log-fundamental values (or simply fundamental values) (Day & Huang, 1990). The first term at the right-hand side of (5) and (6) represents market distortion at time *t*, which computes the deviation of index prices from their fundamentals, $dist_t = f_t - p_t$. γ_t^X and γ_t^Z are introduced to capture additional random orders of fundamental trading rules. γ_t^X and $\gamma_t^Z, t = 1, 2, \ldots, T$ are IID normally distributed random variables with mean zero and constant standard deviations σ_γ^X and σ_γ^Z, respectively. It is assumed that fundamental traders can calculate the fundamental values.

The evolutionary part of the model depicts how beliefs are evolving over time (Brock & Hommes, 1998). That is, how agents adapt their beliefs and switch between strategies. Belief adaptation is mirrored in the fractions w_t; $w_t = \{w_t^{Xc}, w_t^{Zc}, w_t^{Xf}, w_t^{Zf}, w_t^0\}$, where w_t^0 represents the fraction of inactive agents and $w_t^{Xc}, w_t^{Zc}, w_t^{Xf}, w_t^{Zf}$ are as indicated in (1) and (2). Fractions are updated according to evolutionary fitness measures (or attractiveness of the trading rules) which can be presented as

$$A_t^{Xc} = (\exp(p_t^X) - \exp(p_{t-1}^X))D_{t-2}^{Xc} - tax^X(\exp(p_t^X) - \exp(p_{t-1}^X))|D_{t-2}^{Xc}| + mA_{t-1}^{Xc}, \tag{7}$$

$$A_t^{Xf} = (\exp(p_t^X) - \exp(p_{t-1}^X))D_{t-2}^{Xf} - tax^X(\exp(p_t^X) - \exp(p_{t-1}^X))|D_{t-2}^{Xf}| + mA_{t-1}^{Xf}, \tag{8}$$

$$A_t^{Zc} = (\exp(p_t^Z) - \exp(p_{t-1}^Z))D_{t-2}^{Zc} - tax^Z(\exp(p_t^Z) - \exp(p_{t-1}^Z))|D_{t-2}^{Zc}| + mA_{t-1}^{Zc}, \tag{9}$$

$$A_t^{Zf} = (\exp(p_t^Z) - \exp(p_{t-1}^Z))D_{t-2}^{Zf} - tax^Z(\exp(p_t^Z) - \exp(p_{t-1}^Z))|D_{t-2}^{Zf}| + mA_{t-1}^{Zf}, \tag{10}$$

and

$$A_t^0 = 0, \tag{11}$$

where A_t^{Xc}, A_t^{Zc}, A_t^{Xf}, A_t^{Zf}, and A_t^0 are the fitness measures of following chartist strategy in market *X*, chartist strategy in market *Z*, fundamental strategy in market *X*, fundamental strategy in market *Z*, and no-trade strategy, respectively. Inactive traders got zero attractiveness for abstaining from trading. The fitness measure of the other two trading rules; the technical and the fundamental analysis, depends on two components. The first term of the right-hand sides of (7) – (10) is the performance of the strategy rule in most recent time. Notice that orders submitted in period $t-2$ are executed at the price declared in period $t-1$. Gains or losses are recognized according to prices announced in period t. The second term of the right-hand side of (7) – (10) represents agents' memory, where $0 \leq m \leq 1$ is the memory parameter that measures the speed of recognizing current myopic profits.

Loss-aversion behavioral bias is proposed, inspired by Selim, et al. (2015), where chartists evaluate their strategy fitness in terms of a value function of gains and losses [c.f. Tversky and Kahneman (1991), and Benartzi and Thaler (1993)]. The proposed value function implies that the pain of losses is twice the satisfaction of equivalent gains. Therefore, the attractiveness of technical strategy is given by

$$v_t^{Xc} = \begin{cases} A_t^{Xc} & if\ A_t^{Xc} \geq 0 \\ \lambda A_t^{Xc} & if\ \ A_t^{Xc} < 0 \end{cases}, \qquad (12)$$

$$v_t^{Zc} = \begin{cases} A_t^{Zc} & if\ A_t^{Zc} \geq 0 \\ \lambda A_t^{Zc} & if\ \ A_t^{Zc} < 0 \end{cases}, \qquad (13)$$

where $\lambda > 1$ is the parameter of loss aversion that measures the relative sensitivity to gains and losses. However, setting λ = 1 reduces the value functions to $v_t^{Xc} = A_t^{Xc}$ and $v_t^{Zc} = A_t^{Zc}$; this case can be called loss-neutral chartists (Selim, et al., 2015).

Following Manski and McFadden (1981), market share of each strategy can be obtained by the discrete-choice model as

$$w_t^{Xc} = \frac{\exp(rv_t^{Xc})}{1 + \exp(rv_t^{Xc}) + \exp\left(rA_t^{Xf}\right) + \exp(rv_t^{Zc}) + \exp\left(rA_t^{Zf}\right)}, \qquad (14)$$

$$w_t^{Xf} = \frac{\exp(rA_t^{Xf})}{1 + \exp(v_t^{Xc}) + \exp\left(rA_t^{Xf}\right) + \exp(rv_t^{Zc}) + \exp\left(rA_t^{Zf}\right)}, \qquad (15)$$

$$w_t^{Zc} = \frac{exp(rv_t^{Zc})}{1 + exp(rv_t^{Xc}) + exp\left(rA_t^{Xf}\right) + exp(rv_t^{Zc}) + exp\left(rA_t^{Zf}\right)}, \qquad (16)$$

$$w_t^{Zf} = \frac{exp(rA_t^{Zf})}{1 + exp(v_t^{Xc}) + exp\left(rA_t^{Xf}\right) + exp(rv_t^{Zc}) + exp\left(rA_t^{Zf}\right)}, \qquad (17)$$

and

$$w_t^0 = 1 - w_t^{Xc} - w_t^{Zc} - \ w_t^{Xf} - \ w_t^{Zf}. \qquad (18)$$

Trading strategy weights are proportional to strategy attractiveness. Parameter r, in (14) – (18) is called the intensity of choice and it measures the agent's sensitivity to select the trading strategy with higher fitness measure.

3. Simulation Results and Analyses

3.1. Calibration and Simulation Design

In this section, the model is validated by investigating the extent to which it is able to replicate the stylized facts observed empirically. The values of model parameters are chosen so that the model can mimic the dynamics of real financial markets. For the detailed declaration of the idea behind choosing specific values of the parameters, the reader can refer to Westerhoff and Dieci (2006).

The proposed artificial financial market is implemented using NetLogo platform (Wilensky, 1999). At initialization, all parameters of the model are equal to the values defined in Table 1. The performance of 1000 simulation runs is investigated. Each run contains 5000 daily observations. In the following, the evolutionary dynamics of the proposed model is discovered.

3.2 Stylized Facts Replication

Before engaging in a comprehensive Monte Carlo simulation, it is important first to observe a representative simulation run. Figures 1 – 8 depict the behavior of this specific run. Figure 1 illustrates the evolution of log-prices for the two markets. Note that, prices oscillate around their fundamental values. Average market distortion can be computed as $dist = {}^{1}/_{T} \sum_{t=1}^{T} |dist_t|$, which exhibits a value of 11.49 percent for $dist^X$ and a value of 8.54 percent for $dist^Z$. The two price series are random walk and display bubbles and crashes. These results are in good agreement with the stylized facts observed empirically.

---------- Figure 1 should be about here ----------

Figure 2 displays returns of the two markets. It can be observed that extreme returns reach up to ± 20 percent and ± 10 percent for market *X* and *Z*, respectively. Following Guillaume, et al., (1997), volatility can be calculated as average absolute returns (vol) $vol = \frac{1}{T} \sum_{t=1}^{T} |r_t|$. The computed average volatilities are 1.35 and 1.07 percent for vol^X and vol^Z, respectively, indicating excess volatility feature (Shiller, 1981). Also, Figure 2 shows another stylized fact of asset markets, which is volatility clustering.

---------- Figure 2 should be about here ----------

Figure 3 depicts market shares of the five trading strategies. First panel in Figure 3 displays the average weights, which are computed as 20, 25.6, 19.2, 20.4, and 14.8 percent for w_t^{Xc}, w_t^{Xf}, w_t^0, w_t^{Zf}, and w_t^{Zc}, respectively. Note the higher volatility in market *X* than that in market *Z*, which can be explained by the higher participation of chartists in market *X* than that in market *Z*. Additionally, these results show that 34.8 (46) percent of the agents follow technical (fundamental) trading. The effect of loss-aversion behavioral bias can be explored by running a simulation using the same random seeds and the parameter setting illustrated in Table 1 except for $\lambda = 1$. Differences in the dynamics are merely due to loss-aversion behaviour. The second panel in Figure 3 depicts the average market shares, which are computed as 22.9, 17.2, 17.5, 18.7, and 23.6 percent for w_t^{Xc}, w_t^{Xf}, w_t^0, w_t^{Zf}, and w_t^{Zc}, respectively. Henceforth, 46.5 (35.9) percent of the agents follow technical (fundamental) trading. Accordingly, loss aversion causes agents to prefer fundamental trading over technical trading. The increased shares of chartists come at the cost of increased market volatilities, which are computed as 1.38 and 1.11 percent for $vol^X$and vol^Z, respectively.

However, the results of 1000 simulation runs using different random seeds and the parameter setting displayed in Table 1 reveal that the mean of average weights is estimated as 17 percent for w_t^{Xc}, 23 percent for w_t^{Xf}, 20 percent for w_t^0, 23 percent for w_t^{Zf}, and 17 percent for w_t^{Zc}. Thereafter, 34 percent of the agents follow technical trading. Moreover, 46 percent of the agents preferred fundamental trading. As the two markets are assumed to be symmetric, chartists and fundamentalists are equally participated in both markets. Subsequently, no market is preferred over the other. In addition, the reduction in technical trading can be due to the loss-aversion behavior.

---------- Figure 3 should be about here ----------

Another significant stylized fact is power-law tails, with a tail index somewhere in the region 2-5. The exponent α of the Pareto distribution for the tails can be expressed by the following inverse cubic law;

$$Prob(|r_t| > x) \sim x^{-\alpha_r}, \tag{19}$$

with $\alpha_r \approx 3$ [c.f. Lux and Marchesi (1999), Lux (2009), Haas and Bigorsch (2011)]. To check the power-law tails, Hill-index tail estimate is calculated for the smallest and largest 10 percent of the observations. Figure 4 illustrates Hill-index tails estimation process [c.f. Hill (1975) and Huisman, et al., (2001)]. Regression on the smallest (largest) 10 percent of the observations yields a value of 2.85 ± 0.049 (2.40 ± 0.048) for market *X* and a value of 4.09 ± 0.079 (3.51 ± 0.072) for market *Z*. These results are in good accordance with the inverse cubic law of (19).

---------- Figure 4 should be about here ----------

Another astonishing stylized fact to be investigated is the absence of autocorrelation in raw returns. Figure 5 represents autocorrelations for the first 100 lags of raw returns for both markets. The dashed lines present 95 percent confidence bands according to the assumption of a white noise process. The raw returns for the two markets show autocorrelation coefficients, which are not significant over 100 lags. This implies the randomness of asset prices.

---------- Figure 5 should be about here ----------

To study the predictability of asset volatility, autocorrelation in absolute returns is studied. The two panels in Figure 6 depict autocorrelations for the first 100 lags of absolute returns for the two markets. The dashed lines present 95 percent confidence bands according to the assumption of a white noise process. The panels show that absolute returns are significantly autocorrelated for up to 100 (30) lags in market *X* (*Z*). Thus, volatility can be partially predicted (with no significant prediction of the direction of price movements).

---------- Figure 6 should be about here ----------

Another important fact of the financial markets is self-similarity as recognized by Mandelbrot (1983). To investigate self-similarity, detrended fluctuation analysis (DFA) is performed following Peng et al. (1994). Linear relationship on a log-log scale between the average fluctuation F_n, and the time scale, *n*, shows scaling structure of asset returns. Figure 7 depicts the estimation of the scaling exponent, H_r, for raw returns of markets *X* and *Z*. A value of H = 0.5 indicates a white-noise process, a value of 0.5 < H < 1 corresponds to long-range power-law autocorrelations, and a value of 0 < H < 0.5 indicates that large and small oscillations of the time series are very likely to alternate. The scaling exponent H_r yields a value of 0.50 ± 0.029 for market *X* and a value of 0.52 ± 0.005 for market *Z*. Consequently, estimated values of the scaling exponent show white-noise processes.

---------- Figure 7 should be about here ----------

Figure 8 presents the estimation of the scaling exponent, $H_{|r|}$, for absolute asset returns. The scaling exponent $H_{|r|}$ yields a value of 0.89 ± 0.090 for market *X* and a value of 0.73 ± 0.068 for market *Z*. Estimated values of the scaling exponent indicate long-range power-law autocorrelations in absolute returns.

---------- Figure 8 should be about here ----------

Thereafter, the simulation run illustrated in Figures 1 – 8 imitates the behavior observed in real financial markets remarkably well. In what follows, the robustness of these results is investigated by performing a thoroughly Monte Carlo analysis. The analysis relies on 1000 simulation runs, each comprising 5000 observations. All simulation runs are executed with the parameter setting offered in Table 1 using different seeds of the random variables.

Table 2 reports estimates of the mean and the median of the mean, maximum, minimum, standard deviation, skewness, and kurtosis for the two markets. Estimates of the mean and the median of the kurtosis for the two return series are all greater than 3, indicating leptokurtosis.

---------- Table 2 should be about here ----------

Table 3 illustrates estimates of the mean and the median of the Hill tail-index estimators $\hat{\alpha}_k$ for $k \in \{2.5, 5, 10\}$ percent of the smallest (left tail) and largest (right tail) returns for the two assets. For example, considering the smallest (largest) 5 percent of observations of r^X, estimate of the tail index displays a value of 3.63 (3.09) for the median. The results show that average Hill tail-index estimates of the largest and smallest 10 percent observations are in good agreement with the universal cubic law (see (19)).

---------- Table 3 should be about here ----------

Table 4 displays estimates of the mean and the median of autocorrelation in raw returns, $\mathrm{AC}_{\mathrm{r}}^{\ell}$, for lags $\ell \in \{1,2,3\}$, and autocorrelation in absolute returns, $\mathrm{AC}_{|\mathrm{r}|}^{\ell}$, for lags $\ell \in \{1,20,50,100\}$. Estimates of the median of autocorrelation coefficients $\mathrm{AC}_{\mathrm{r}}^{\ell}$ indicate that price changes are mainly uncorrelated. For instance, estimate of the median of autocorrelation coefficients $\mathrm{AC}_{\mathrm{r}}^{1}$ reveals a value of 0.03 for r^X and a value of 0.03 for r^Z This is in line with most real financial markets, where asset price evolves according to a random walk. Estimate of the median of autocorrelation coefficients $\mathrm{AC}_{|\mathrm{r}|}^{1}$ reveals a value of 0.28 for r^X and a value of 0.28 for r^Z, indicating persistence in volatility.

---------- Table 4 should be about here ----------

Finally, the robustness of the scaling behavior and the fractal structure is needed to be checked. Table 5 displays estimates of the mean and the median for the scaling exponent of raw returns, H_r, and the scaling exponent of absolute returns, $H_{|r|}$. Estimate of the median of H_r reveals a value of 0.50 for r^X and a value of 0.49 for r^Z. These figures indicate a small degree for predicting asset returns. Furthermore, estimate of the median of $H_{|r|}$ reveals a value of 0.79 for r^X and a value of 0.78 for r^Z. These values display long-range power-law autocorrelations in absolute returns.

---------- Table 5 should be about here ----------

Summing up, the model replicates the stylized facts of real financial markets remarkably well. Thereafter, the model can serve as a testbed to examine the effect of levying transaction taxes on the agents' switching behavior. For this purpose, two scenarios are to be investigated. *First*, the impact of imposing taxes in one market only. *Second*, the impact of imposing taxes in the two markets. The results of these scenarios are illustrated in the following section.

4. The Dynamics with Transaction Taxes

4.1 Transaction Taxes in One Market

To explore the impact of imposing transaction taxes in one market only, a transaction tax of 0.25 percent is imposed in one market, e.g. market *X* (as the two markets are assumed to be symmetric, the results would not be changed if market *Z* is selected). Figure 9 displays a simulation run using the same random seeds for the simulation presented in Figures 1 – 8. The simulation is executed based on the parameter setting presented in Table 1 except for $tax^X = 0.0025$. Thereafter, differences in the dynamics are merely due to taxation. Figure 9 can be compared directly with Figures 1,2, and the first panel in 3. The first two panels in Figure 9 show evolution of log prices. Price bubbles and market crashes can be observed. Moreover, prices oscillate around their fundamentals. The third and fourth panels in Figure 9 show asset returns. The return series exhibit excess volatility and clustered volatility as observed in real financial markets. The last panel in Figure 9 illustrates market shares of the five trading strategies. No trading strategy dominates the others. Surprisingly, the average weights are computed as 20, 25.6, 19.2, 20.4, and 14.8 percent for w_t^{Xc}, w_t^{Xf}, w_t^0, w_t^{Zf}, and w_t^{Zc}, respectively. Additionally, the computed average volatilities are 1.35 and 1.07 percent for vol^X and vol^Z, respectively, and the computed average market distortions are 11.49 and 8.54 percent for $dist^X$ and $dist^Z$, respectively. These are the same figures obtained from the simulation run presented in Figures 1 – 8. Thereafter, levying taxes in one market does not affect market dynamics in both markets.

---------- Figure 9 should be about here ----------

To check the robustness of these results, a comprehensive Monte Carlo analysis is applied. The analysis relies on 1000 simulation runs for each tax rate, which is increased from 0.05 to 0.5 in 20 steps. Each simulation is comprised of 5000 observations. All simulation runs are executed based on the parameter setting offered in Table 1 using different seeds of the random variables. Figure 10 depicts the results of the Monte Carlo simulation for the first scenario. Figure 10 displays average volatility for both markets, average price distortion for both markets, and average weights of the five trading strategies. The first panel in Figure 10 depicts that volatility of both markets fluctuate around 1.18 percent. Which tax rate would stabilize the markets? There is no specific tax rate that would decrease volatility in both markets at the same period. However, there is no tax rate that cause drastic increase in market volatility. The same result is observed from the second panel in Figure 10. No significant deviation in market distortion can be noticed. The last panel in Figure 10 indicate market shares of trading strategies, which are around 46, 20, and 34 percent for fundamentalists, chartists, and inactive traders, respectively. In addition, chartists and fundamentalists are almost equally participated in both markets. Thereby, imposing transaction taxes in one market may not affect market stability or price distortion. Moreover, there is no strong evidence that traders would prefer trading in the market without transaction taxes. The traders, also, prefer fundamental trading over technical trading. However, this is the same result obtained from the model without introducing transaction taxes.

---------- Figure 10 should be about here ----------

4.2. Transaction Taxes in Both Markets

To explore the impact of imposing transaction taxes in the two markets, a transaction tax of 0.25 percent is imposed in both markets. Figure 11 displays a simulation run based on the same random seeds of the simulation run depicted in Figures 1 – 8 using the parameter setting presented in Table 1 except for $tax^X = 0.0025$ and $tax^Z = 0.0025$. Thereby, differences in the dynamics are only due to taxation. Figure 11 can be compared directly with Figures 1,2, and the first panel in 3. The first two panels in Figure 11 depict log price evolution. Prices oscillate around their fundamentals and resemble the behavior of asset prices observed empirically. The third and fourth panels in Figure 11 illustrate asset returns, which exhibit excess volatility and volatility clustering as observed in real financial markets. The last panel in Figure 11 illustrates the market shares of the five trading strategies. Amazingly, the average weights are computed as 20, 25.6, 19.2, 20.4, and 14.8 percent for w_t^{Xc}, w_t^{Xf}, w_t^0, w_t^{Zf}, and w_t^{Zc}, respectively. Additionally, the computed average volatilities are 1.35 and 1.07 percent for vol^X and vol^Z, respectively. The computed average market distortions are 11.49 and 8.54 percent for $dist^X$ and $dist^Z$, respectively. These are the same figures obtained from the simulation run presented in Figures 1 – 8 and 9. Thereafter, levying taxes in the two interacting markets does not affect market dynamics in both markets.

---------- Figure 11 should be about here ----------

The robustness of these results is checked by applying a thorough Monte Carlo analysis. The analysis relies on 1000 simulation runs for each tax rate, which is increased from 0.05 to 0.5 in 20 steps. Each simulation is comprised of 5000 observations. All simulation runs are executed based on the parameter setting offered in Table 1 using different random seeds. Figure 12 depicts the results of the Monte Carlo simulation for the second scenario. Figure 12 shows average volatility for both markets, average price distortion for both markets, and average weights of the five trading strategies. The first panel in Figure 12 depicts that volatility of both markets fluctuate around 1.18 percent. In addition, different values of tax rates have slight effect on market volatilities in either direction. The same result is obtained for price distortions. No significant deviation in market distortion can be noticed from the second panel in Figure 12. As indicated by the last panel in Figure 12, market shares of trading strategies are around 46, 20, and 34 percent for fundamentalists, chartists, and inactive traders, respectively. Furthermore, chartists and fundamentalists are almost equally participated in the two markets. Thus, imposing transaction taxes in two interacting markets may not cause instability or price distortion in both markets. Moreover, the traders prefer fundamental trading over technical trading. Nevertheless, this is the same result obtained in the artificial markets with zero taxes and with a levy in one market only.

---------- Figure 11 should be about here ----------

5. Conclusions

In this paper a behavioral agent-based model is proposed to provide a suitable testbed for policy makers. The proposed framework models the interaction between two different financial markets; market *X* and market *Z*. There are two types of agents populating the artificial markets; traders and market makers. Each time step, traders decide on one of the trading strategies; (i) technical trading in market *X*, (ii) fundamental trading in market *X*, (iii) technical trading in market *Z*, (iv) fundamental trading in market *Z*, or (v) abstain from trading. The market share of each trading strategy is determined according to past and current performance of this strategy. As chartists are loss averse, losses loom larger than equivalent gains. This behavioral bias affects agent switching behavior among trading strategies, which consequently enhances market stability. The discrete-choice model is followed to compute market shares of trading strategies. Market makers update asset prices according to the net submitted orders. A log-linear price impact function is followed to settle asset prices. The proposed model can replicate stylized facts observed empirically such as, bubbles and crashes, excess volatility, volatility clustering, absence of autocorrelation in raw returns, persistence in volatility, power-law tails, and fractal structures. Thereby, the model can be used as a testbed to investigate the effect of applying regulatory policies. Tobin transaction tax is introduced and its impact on market dynamics is explored. For this purpose, two scenarios are considered; (i) levying a transaction tax in one market only and (ii) levying transaction taxes in the two markets. The results show that imposing transaction taxes in either scenario would affect market shares of trading strategies, distortion, or volatility. Thereafter, imposing small transaction taxes would generate revenues and may not affect market dynamics. The results are in good agreement with Tobin’s suggestions.

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