SAND IN THE WHEELS OR THE WHEELS IN SAND? TOBIN TAXES AND MARKET CRASHES

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Abstract

Recent crisis revived interest in financial transaction taxes (FTTs) as a means to offset negative risk externalities. However, up-to-date academic research does not provide sufficient insights into the effects of transaction taxes on financial markets, as the literature has here-to-fore been focused too narrowly on Gaussian variance as a measure of volatility. In this paper we argue that it is imperative to understand the relationship between price jumps, Gaussian variance, and FTTs. While Gaussian variance is not necessarily problem in itself, the non-normality of return distribution caused by price jumps affects not only the performance of many risk-hedging algorithms but directly influences the frequency of catastrophic market events. To study the aforementioned relationship we use an agent-based model of financial markets. Its results show that FTTs may increase the variance while decreasing the impact of price jumps. This result implies that regulators may face a trade-off between overall variance and price jumps when designing optimal tax.

Keywords: price jumps, financial transaction taxes, agent-based modeling, Monte Carlo, volatility.

JEL Classification Number: C15, C16, C61, G17, G18

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Abstract

Současná finanční krize opět oživila zájem o daně z finančních transakcí (FTT) jako způsob jak vykompenzovat negativní externality z rizika propadu finančních trhů. Akademický výzkum ale nedává uspokojivou odpověď ohledně efektů těchto daní na finanční trhy, protože literatura se soustředila výhradně na gaussovskou varianci jako míru volatility. V tomto článku odůvodňujeme, že je důležité porozumět vztahu mezi cenovými skoky, gaussovskou varianci a FTT. Zatímco samotná gaussovská variance nemusí představovat problém, nenormalita distribuce výnosů zapříčiněná cenovými skoky ovlivňuje nejenom efektivnost mnohých zajišťovacích algoritmů, ale má taky přímý vliv na frekvenci krachu finančních trhů. K studiu tohoto vztahu využíváme multiagentního modelu finančních trhů. Ukazujeme, že FTT můžou zvýšit varianci a zároveň snížit dopad cenových skoků. Tento výsledek naznačuje, že regulační orgány mohou při tvorbě optimální daně čelit potřebě kompromisu mezi celkovou variancí a cenovými skoky.
1 Introduction

Nobel laureate James Tobin first proposed a tax on spot conversions of one currency into another (Tobin, 1978) in the aftermath of the Bretton-Woods system’s break-up as a way to mitigate short-term financial round-trip excursions into another currency. His intention was “to throw some sand in the wheels of our excessively efficient international money markets.” He and his co-authors offered more arguments in favor of the tax in Eichengreen et al. (1995). But Tobin’s idea was just a specific application of Keynes’s idea of a tax on transactions mitigating the effect of speculation on financial markets (Keynes, 2006). However, the name ‘Tobin tax’ is today often used to denote not only foreign exchange transaction taxes, but financial transaction taxes (FTTs) in general. Therefore, the following text uses these terms interchangeably.

The debate on merits of Tobin-like taxes has not so far reached a definite conclusion. The proponents of the tax claim that increased transaction cost affects short-term high volume trading (speculation) more than long-term positions, decreasing market volatility and thus potential for crashes. In this regard the tax can be thought of as a Pigovian tax on a negative risk externality, as increased volatility can decrease welfare and efficiency. The opponents of the Tobin tax generally claim that it can, in fact, increase volatility by decreasing market liquidity or that speculative trading serves to stabilize prices around long-run equilibrium. Although recently quite widely discussed in policy and political circles, the debate there is often driven by ideology and politics rather than rigorous academic research. The academic debate was historically driven mostly by theoretical models, although more recently simulation and empirical studies have been gaining some ground. However both theoretical predictions and empirical evidence is so far mixed.

Historically, one strand of the literature used macroeconomic models of market bubbles. The arguments against the tax are often based on efficient market hypothesis (EMH from now on; due Fama, 1965), which implies that speculators cannot destabilize market, as they would eventually run out of money and be driven out of the market. Furthermore, based on EMH one can argue that speculative trading provides liquidity and helps to incorporate new information into the prices. Opposing models argue that externalities, imperfect information and other frictions may cause inefficiencies and that in these cases FTTs can help economy reach the second best outcome.

Another strand of literature is focused on microeconomic behavior of the agents of the financial markets. Earlier examples of heterogeneous agent models include Palley (1999), who combined noise traders (which were shown in prior literature to increase volatility, see e.g. De Long et al., 1990) with the literature analyzing the Tobin tax. He identified conditions under which such a tax drives out noise traders, thus benefiting fundamental traders and lowering volatility and leading to higher efficiency. Also, he concluded that there is a trade-off between costs and benefits, because Tobin tax may discourage fundamental traders, as well. Westerhoff (2003) used model with fundamentalist and chartist traders in...
a model of foreign exchange markets. In this model, a low tax rate first crowds out chartism, but higher rates lead to misalignment due to decreasing number of fundamentalist. Using a different approach, Mathevet and Steiner (2012) show on a dynamic global game that in the imperfect information setting transaction taxes may stop sudden investment reversals under certain conditions, thus increasing welfare.

The empirical evidence on this issue is scant (one of the reasons is that it has never been adopted in its true form as a global tax) and, as we will argue, methodologically problematic. Few papers that tried to estimate the effect empirically (estimating effect of transaction taxes either on local foreign exchange or financial markets) offer support for all possible sides of the debate. The side that found evidence against the transaction tax includes Umlauf (1993) who, based on time series data on equity returns in Sweden, found that by introducing transaction tax the volatility measured by the conditional variance went up and trading volumes down. Moreover, the author argued that significant amount of trading activity moved to London. However, it must be noted that Swedish transaction tax of 1% (later increased to 2%) was higher than what Tobin proposed originally (0.5%), and the author himself notes that “appropriate theoretical foundations are lacking” making the estimation imprecise and warns against “generalizing from a single data point” (ibid. p. 239). Aliber et al. (2002) examined the effect of transaction costs in general on volatility (defined as standard deviation of prices) of foreign exchange rates for four different currencies, and found positive relationship as well. The opposite result, in support of proponents of the Tobin tax, can be found in Liu and Zhu (2009) who found that lowering of transaction costs in Japan lead to higher volatility, implying negative correlation between transaction costs and volatility. Finally, third group of literature have not found any significant effect — see e.g. Hu (1998), who studied effects of stock transaction tax on market volatility and turnover taking advantage of 14 tax changes that occurred in stock markets in Hong Kong, Japan, Korea, and Taiwan during the period 1975-1994.

We see two major issues that are left rather unexplored. First, scale effect arguably plays a major role in the (Tobin tax was meant to be a global tax). Small markets like Sweden does not have a significant impact on the world economy, so the speculative trading moves abroad, it does not alter the volatility on these foreign markets, but may very much hurt trade volumes domestically. However, if the market is large enough, there will be an impact on foreign market as well. Second, perhaps more importantly, we argue that the studies ignored a significant source of information by focusing on conditional variance as a single measure of volatility. Concerning the first point, some work has been already done. Westerhoff and Dieci (2006) studied the phenomenon in a model with heterogeneous agents who can trade in different markets and can choose a trading strategy (e.g. fundamentalist vs. chartist). Importance of strategies evolve over time according to their fitness. They find that the tax decreases volatility in the market where it was imposed while increasing it on the other. The opposite effect of transaction tax on volatility in the two market framework was obtained by Mannaro et al. (2008), who used the methodology of

1Note although the tax rate was initially 0.5% and later increased to 1%, this tax was nominally borne by both sides of the transaction implying the overall tax rate of 1% and 2%, respectively.
agent-based models (ABMs). They used four types of traders with different strategies, who can trade on the maximum of two markets. However the relative share of strategies is exogenously input by the authors, but agents may choose where to trade and whether to trade at all. On the other hand, one of the few most recent studies, Bianconi et al. (2009), concluded that transaction tax decreases volatility. Their ABM based on Minority Game framework used again fixed strategies that were randomly distributed across agents at the beginning of the simulation.

Our second – more important and thus far unexplored – point is that all of these studies focused on conditional Gaussian variance as a measure of volatility. They ignore additional source of volatility—price jumps. The literature suggests (Merton [1976] or Giot et al. [2010]) that volatility of most financial instruments can be decomposed into two parts: a regular Gaussian component and a price jump component. Many models aim to estimate conditional variance, such as various GARCH models ignore the price jump component while allowing the realized variance to deviate from the Gaussian distribution. However, as we show in this paper, the link between price jumps and conditional variance is not that straightforward – the measure of one may rise while the measure of the other decreases. Higher conditional variance does not have to be a problem per se, because it does not necessarily lead to a leptokurtic return distribution. Fat tails, which have become a stylized fact of financial markets, are better explained by price jumps, so even if the transaction tax increases conditional variance, its effect on price jump frequency may be opposite, thus making the distribution less fat-tailed. If this is the case, the tax would not only improve the prediction power of standard asset pricing models that use normal distribution but, given that catastrophic events are non-normal in nature, it would lead to higher stability of financial markets. However, the relationship between transaction taxes and price jumps has here-to-fore been rather ignored in the literature.

This paper argues that it is crucial to understand the effect of the Tobin tax on price jumps. As Andersen et al. (2002, 2007) show, price jumps are present in majority of price time series, therefore their presence should be a subject of research. Price jumps can have serious adverse impact on predictive power of the pricing formulas and calculation of the estimates of the financial variables. Moreover, price jumps are the source of non-normality and may cause black-swan events on financial markets.\(^3\)

While the presence of price jumps in the data is well established, the literature disagrees on their origin. One branch of literature (Merton [1976] Lee and Mykland [2008] or Lahaye et al. [2011]) considers new information a primary source of price jumps, while other authors, like Joulin et al. (2008) and Bouchaud et al. (2006), conclude that price jumps are mainly caused by a local lack of liquidity with news announcements having a negligible effect. The third branch – behavioral finance literature (e.g. Shiller [2005]) – suggests that price jumps are caused by the behavior of market participants themselves.

\(^2\)For an overview see Hamilton (1994).  
\(^3\)For illustrations of changes in the pricing formulas caused by price jumps see Pan (2002) or Broadie and Jain (2008).  
Brooks et al. (2011) discuss the effect of higher moments on optimal allocations within utility-based framework.
For analyzing the two latter views the ABM methodology is especially appropriate, since it allows for explicit modeling of interactions among market participants.

The principal contribution of this paper is to study the relationship between price jumps and variance, and how transaction taxes affect them. The rest of the paper is organized as follows. We describe the agent based model for simulation of the artificial financial markets in Section 2. In Section 3, we model the impact of the FTT on the price process and provide estimators to quantify this effect. Section 4 discusses results of our analysis. We discuss the importance of the results and avenues for further research in Section 5.

## 2 Model of financial transaction tax

In order to better understand the effect of the FTTs on prices, we now introduce these taxes to the price process widely used in the finance literature.

### 2.1 Model of price process

Throughout this paper, we consider a one-dimensional asset log-price process $X_t$ that takes the form of the Ito semimartingale described by the following stochastic differential equation:

$$
\begin{align*}
&dx_t &= \mu_t dt + \sigma_t dB_t + \int_{\mathbb{R}} x \mu_t (dt, dx) , \\
&\text{(1)}
\end{align*}
$$

where $B(t)$ is a standard Brownian motion. The spot volatility $\sigma_t$ is a càdlàg process bounded away from zero almost surely. The drift $\mu_t$ is in our case identically equal to zero. Variable $\mu (dt, dx)$ is an integer-valued random measure that captures a jump in $X_t$ over a time interval $[t, t + dt)$. This implies that a jump arrives to the market whenever $\Delta X_t \equiv X_t - X_{t-} \neq 0$. Let us further define a jump intensity $dt \otimes \nu_t (dx)$, where $\nu_t (dx)$ is some non-negative measure with a constraint $\int_{\mathbb{R}} (x^2 \wedge 1) \nu_t (dx) < \infty$. More precisely, we assume large price jumps with finite activity. As a result, for any fixed interval $[0, T]$ there is a finite number of time moments $t$ such that $\Delta X_t \neq 0$.

For a certain fixed interval $[0, T]$ the jump term with corresponding jump intensity $\nu_t$ gives rise to a finite number of price jumps. More precisely, there exists a finite number $t_i \in [0, T]$ such that $U_i \equiv \Delta X_{t_i} > 0$ in the limit, with $i = 1, \ldots, N_T$. In such a case, there are exactly $N_T$ price jumps. The term $\nu_t$ thus affects both the $U_i$, and the grid $T_i = \{t_1, \ldots, t_{N_T}\}$ including its cardinality.

The Tobin tax in the model affects the trading and thus the random processes in Eq.(1). In particular, the process driving the volatility and the jump measure depends on the tax rate $\tau$:

---

4 The fundamental price in our model is fixed, which is equivalent to a world with zero deterministic interest rates. Alternative and equivalent explanation is that our model describes detrended data.
\[\sigma_t \to \sigma_t(\tau) \quad \nu_t \to \nu_t(\tau). \tag{2}\]

Estimation of the functional dependence between the spot processes in (2) and the FTT is not a straightforward task, as the randomness in the spot processes would be a confounding factor. Any test would therefore require a comparison of the random processes that depend on the current state of the world. To tackle these issues, we use integrated variables.

Two integrated variables are of particular interest in this context: quadratic variance and integrated variance. For the log-price \(X_t\) specified by Eq.(1) defined over a time interval \([0, T]\), we define quadratic variance as:

\[QV_T(\tau) = \int_0^T \sigma^2_s(\tau) \, ds + \sum_{i=1}^{N_T} U^2_i(\tau), \tag{3}\]

where we keep the explicit functional dependence on the Tobin tax. Quadratic variance captures contributions both from the spot volatility \(\sigma_t(\tau)\) and from the jumps. Integrated variance, on the other hand, is defined as:

\[IV_T(\tau) = \int_0^T \sigma^2_s(\tau) \, ds, \tag{4}\]

Thus, integrated variance is defined as an integral over the square of continuous-time spot volatility.

The difference between \(IV_T\) and \(QV_T\) forms the basis of price jump detection.\(^6\) For this purpose, however, we need consistent estimators of \(QV_T\) and \(IV_T\) under the log-price process (1). Therefore, let us define realized quadratic variance as:

\[\hat{RV}_{M,T} = \sum_{i=1}^{M} \left( Y_{i,T} - Y_{(i-1),T} \right)^2. \tag{5}\]

Then for any sequence of non-stochastic partitions \(0 = t_0 < t_1 < \cdots < t_M = T\) that satisfies \(\sup(t_i - t_{i-1}) \to 0\) as \(M \to \infty\), the log-price process \(X_t\) defined over a time interval \([0, T]\) sampled into \(M\) equidistant parts exhibits the following property:

\[\hat{RV}_{M,T} \overset{P}{\to} QV_T. \tag{6}\]

Furthermore, let us define realized bipower variance as:

\[\hat{BV}_{M,T} = \mu_1^{-2} \sum_{i=2}^{M} \left| Y_{i,T} - Y_{(i-1),T} \right| \left| Y_{(i-1),T} - Y_{(i-2),T} \right|. \tag{7}\]

\(^{5}\)Recall that \(\sigma_t\) itself is a random process with a structure similar to the log-price equation.

\(^{6}\)See Barndorff-Nielsen and Shephard (2006).
where \( \mu_\alpha = E(|z|^\alpha) \), with \( z \sim N(0,1) \), and \( \mu_1 = \sqrt{2/\pi} \). Barndorff-Nielsen and Shephard (2004) showed that for this definition and the same sequence of \( M \) partitions as above, realized bipower variance possesses the following property:

\[
\bar{BV}_{M,T} \overset{p}{\rightarrow} \text{IV}_T. \tag{8}
\]

Conveniently, the small sample correction coefficient \( \frac{M}{M-1} \) is introduced in the definition (7). The literature provides a plethora of estimators of integrated variance.

### 2.1.1 Estimating numbers of price jumps

Estimating the price jump contribution to the overall quadratic variance is one way how to assess the role of price jumps in the price process. Alternatively, we may directly identify overall amount of price jumps. For a given sampling frequency, we thus assess the cardinality of the set of returns, which contain at least one price jump.

To test for a presence of a price jump in a particular return, we employ a test developed by Lee and Mykland (2008). As Hanousek et al. (2012) argue, this test is optimal with respect to Type-II errors. It is based on the bipower variance suggested by Barndorff-Nielsen and Shephard (2004) for underlying processes following (1). The test statistics is based on the results of extreme value theory. More precisely, the key quantity is the distribution of maximum returns normalized by the spot integrated variance. The spot quadratic variance is estimated using the bipower variance over a moving window capturing the immediate past movements of the price process. Namely, the test statistics developed by Lee and Mykland (2008) is defined as:

\[
\frac{\max_{t \in A_n} |L_t| - C_n}{S_n} \rightarrow \xi, \tag{9}
\]

where \( A_n \) is the tested region with \( n \) observations and \( L_t = r_t/\hat{\sigma}_t \), \( C_n = \frac{(2 \ln n)^{1/2}}{\mu_1} - \frac{\ln \pi + \ln \ln n}{2\mu_1(2 \ln n)^{1/2}} \), \( S_n = \frac{1}{\mu_1(2 \ln n)^{1/2}} \), and \( \mu_1 \), where \( \hat{\sigma}_t \) stands for the spot bipower variance defined as:

\[
\hat{\sigma}_t^2 = \frac{1}{T-1} \sum_{u=t-T+1}^{t-1} |r_u| |r_{u-1}|, \tag{10}
\]

where we use different notation from (7) to explicitly stress the moving window \( u \). Note that the term \( \mu_1^{-2} \) is included in coefficients \( C_n \) and \( S_n \).

Lee and Mykland (2008) show that under the null hypothesis of no price jump, the random variable \( \xi \) follows the standard Gumbel distribution function \( P(\xi \leq x) = \exp(-e^{-x}) \). The number of price jumps detected in this way is then counted for a given window, in our case 120 days.

\[\text{See Dumitru and Urga (2012) for a comprehensive overview.}\]
2.1.2 TVaR

The sensitivity of markets to extreme events can be measured by a widely-used measure of risk – tail value at risk (TVaR). Since the prices in our model can be seen as stochastic deviations from a deterministic trend (which can be thought of as a risk-free instrument price), we can construct the following portfolio.

A hypothetical investor borrows 50 dollars at time \( t \) — the “fair” price of stocks in our model — and uses them to buy stocks. At time \( T \), he sells the stocks and returns the money. Therefore, the difference \( (P_T - P_t) \) can be perceived as the value of the zero investment portfolio over the time horizon \( T - t \). This difference is exactly the return \( r \cdot (T-t) \).

The cumulative distribution function \( F \) of the return \( r \cdot (T-t) \) can be used to define the quantile function as \( Q = F^{-1} \). Then, the TVaR over a period \( (T - t) \) is defined as:

\[
TVaR_p (r) = E \left[ r \cdot (T-t) \mid r \cdot (T-t) \leq VaR_p \right] = \frac{1}{p} \int_0^p Q (1-u) \, du = \frac{1}{p} \int_0^p VaR_u \, du,
\]

The TVaR is an equally weighted average of the returns in the VaR region. It takes into account the magnitude of the losses and therefore it incorporates more information than the pure VaR measure. The TVaR was computed for \( p \)'s of 95%, 99% and 99.9%. To evaluate the integral in Eq.(11) we use numerical integration with 50 points.

2.2 Effects of Tobin tax

We study the effect of the Tobin tax on financial markets through changes in quadratic and integrated variance caused by changes in the tax rate. The convergence of estimators in (6,8) is achieved for every process satisfying the assumptions stated in Eq.(1). We assume that for a reasonable region of the Tobin tax considered in this study, \( \tau \in [0, \bar{\tau}] \), these assumptions hold. Therefore, for every tax rate the asymptotic convergence of (6,8) takes the form:

\[
\forall \tau \in [0, \bar{\tau}] : \quad \frac{\overline{RV}_{M,T} (\tau)}{\overline{BV}_{M,T} (\tau)} \xrightarrow{p} QV_T (\tau) \quad \text{and} \quad \frac{\overline{BV}_{M,T} (\tau)}{\overline{IV}_{M,T} (\tau)} \xrightarrow{p} IV_T (\tau).
\]

Considering well known properties of self-organized systems, we do not impose any assumptions on the continuity or smoothness of the spot variance \( \sigma_t \) and the jump process captured by the jump intensity \( \nu_t \), which are functions of the Tobin tax. As a consequence, the derivative of \( QV_T (\tau) \) and \( IV_T (\tau) \)—or

\footnote{Although value-at-risk, and by extension TVaR, is convenient to use, it is sometimes criticized for failing to meet criteria for a coherent measure of risk (homogeneity, monotonicity, translation invariance and subadditivity). However, \cite{Danielsson2013} show that these measures, in fact, do satisfy these conditions in many practical cases, making them a reasonable choice for our application.}

\footnote{For example, \cite{Lavicka2010} show that such a system may develop phase transitions of the first or second kind.}
their respective estimators—with respect to $\tau$ may not necessarily exist.

Due to the asymptotics \cite{12} for any fixed $\tau \in [0, \bar{\tau}]$, we analyze the dynamics of contribution of price jumps to the total quadratic variance through the $\hat{RV}_{M,T}(\tau)$ and $\hat{BV}_{M,T}(\tau)$, respectively. The variable of interest is the relative contribution of the price jumps to the quadratic variance as a function of $\tau$:

$$\hat{JS}_{M,T}(\tau) \equiv \frac{\hat{RV}_{M,T}(\tau) - \hat{BV}_{M,T}(\tau)}{\hat{RV}_{M,T}(\tau)}.$$ \hspace{1cm} (13)

Then, having estimated $\hat{RV}_{M,T}(\tau)$ and $\hat{JS}_{M,T}(\tau)$, we may assess the effect of the Tobin tax on market volatility.

Table 1: Sensitivity of the $\hat{RV}_{M,T}(\tau)$ and $\hat{JS}_{M,T}(\tau)$ as a function of $\tau$.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\Delta \hat{JS}_{M,T}(\tau_0)$</th>
<th>Case</th>
<th>$\Delta \hat{RV}_{M,T}(\tau_0)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$= 0$</td>
<td>D</td>
<td>$= 0$</td>
</tr>
<tr>
<td>B</td>
<td>$&gt; 0$</td>
<td>E</td>
<td>$&gt; 0$</td>
</tr>
<tr>
<td>C</td>
<td>$&lt; 0$</td>
<td>F</td>
<td>$&lt; 0$</td>
</tr>
</tbody>
</table>

The sensitivity of the volatility to the Tobin tax can be then expressed through the possible combinations of effects on $\hat{RV}_{M,T}(\tau)$ and $\hat{JS}_{M,T}(\tau)$ that can be seen in Table 1. In particular, the combination (A,D) corresponds to no sensitivity of the volatility process—either diffusion or price jumps—to the Tobin tax. All other combinations suggest some form of sensitivity to the Tobin tax. The combinations (B,F) and (C,E) play a special role. In the first case, the overall realized quadratic variance, usually perceived as market volatility, decreases with the increasing tax rate, while the corresponding contribution of price jumps rises. This means that imposing the Tobin tax leads to a decrease in volatility; however, the volatility is less Gaussian. In the latter case, the mechanism is reversed. As a result, the changing contribution of price jumps to the overall volatility can have serious consequences.

3 Agent-based model

We study the relationship between the price process and the FTT discussed in Section 2 using an agent-based model (ABM). ABMs are especially appropriate for the study of the impact of FTTs on financial markets because:

1. They allow for explicit modeling of said transactions (interactions), not relying on market clearing assumption thus allowing us to study behavior out of steady state;

2. They allow for modeling of each agent independently, and every agent can pick their strategies according to the evolution of the modeled system. This implies that these agents are allowed to be heterogeneous both ex ante and ex post
Our basic treatment follows the methodology of Raberto et al. (2003) and Mannaro et al. (2008) with some modifications. We define four types of agents based on their behavior: random traders, fundamentalist traders, momentum traders, and contrarian traders. We use their values of parameters that were calibrated so that the price series generated match the usual stylized facts of financial markets. The agent-based modeling procedure itself is performed as follows (similar to Lavička et al., 2010): We set initial conditions of the model including number of interacting agents and various model-specific parameters described below. Then we let the economy to evolve step by step until a predetermined number of steps (or trading days) are reached. Every step we record closing price, overall traded amount of assets, amount of assets sold and bought by each trader group, total demand and total supply by each trader group, wealth in each trader group, and tax revenue. We repeat this simulation 300 times to obtain statistically robust results. For the actual simulation we use modified Zarja C++ environment for agent-based modeling developed in Lavička (2010) and downloadable from http://sourceforge.net/projects/politeconomy/.

3.1 Trader types

Our artificial market consists of traders distributed evenly into four groups based on their decision rules (random, fundamentalist, momentarian, and contrarian). At any given time $t$, any agent $i$ is characterized by her cash holdings ($c_i(t)$) and asset holdings ($a_i(t)$).

**Random traders** Random traders denoted as $R$ do not follow any particular strategy, they issue a buy or a sell order with equal probability. They are a proxy for traders that trade for their private reasons independent of the market situation, or who follow irrelevant information. If they buy (sell) the limit price of their buy (sell) order is determined as:

$$ l^b_i = p(t) \cdot X, $$

$$ l^s_i = p(t) / X, $$

where $X \sim N(\mu, s_i)$. The standard deviation $s_i$ of this Gaussian distribution is determined as:

$$ s_i = k \cdot \sigma_i(\omega_i), $$

where $\sigma_i(\omega_i)$ is the standard deviation computed based on window length $\omega_i \sim U[2, 5]$. Parameter $k$ is set to 1.9. As Mannaro et al. (2008) argue, the dependence on past variance simulates a GARCH model trading.

The problem may arise when $s_i$ becomes so large that the realization of $N(\mu, s_i)$ becomes negative.
We solve this problem by setting the sell or buy order to zero in these cases.

**Fundamentalist traders** Fundamentalists trade based on their beliefs about the fundamental price of assets. If fundamentalists decide to buy or sell, they buy/sell a fraction $q$ of their inventory, which depends on current ($p(t)$) and fundamental ($p_f$) price of the asset:

$$q = k \cdot \frac{|p(t) - p_f|}{p_f}.$$  \hspace{1cm} (17)

The parameter $k$ is the same as in the random traders’ case. In effect, these traders are arbitrageurs who try to take advantage of differences between market and fundamental price of assets.

**Momentum traders** Denoted as $T$, these traders follow trend — they buy when the price goes up and sell when it goes down. They are a proxy for traders using technical analysis or herd behavior. They look back at the history based on a time window $\omega_i$, which is randomly drawn at the beginning of the simulation. If they decide to issue an order, the limit price $l_i$ is computed as:

$$l_i = p(t) \cdot \left[1 + k \cdot \frac{p(t) - p(t - \tau_i)}{\tau_i p(t - \tau_i)} \right],$$  \hspace{1cm} (18)

where $k$ is the same parameter as before. In this case $\omega_i \sim U[3, 20]$. Conditional on the decision to sell (buy) the exact quantities are computed as follows:

$$q_{s,i}^a = a_i(t) \cdot U \cdot \left[1 + k \cdot \frac{|p(t) - p(t - \tau_i)|}{\tau_i p(t - \tau_i)} \right],$$  \hspace{1cm} (19)

$$q_{b,i}^b = a_i(t) \cdot U \cdot \left[1 + k \cdot \frac{|p(t) - p(t - \tau_i)|}{\tau_i p(t - \tau_i)} \right],$$  \hspace{1cm} (20)

where $q_{s,i}^a$ is the quantity to sell and $q_{b,i}^b$ is the quantity to buy, and $U$ follows uniform distribution $U(0, 1)$. Naturally, agents cannot sell more assets than they possess ($q_{s,i}^a \leq a_i(t)$), nor spend more cash than they hold ($q_{b,i}^b \leq c_i(t)$).

**Contrarian traders** Similarly to momentum traders, contrarian traders (C) follow technical analysis of the trend, however they expect that if the price is rising it is going to fall soon, so they try to sell near the maximum and vice versa. This implies that their behavioral rules are the same as those of momentum traders, only in the opposite direction.

### 3.2 Tax collection

The tax rate is imposed on both sides of the transaction. More precisely, it is added on top of the price for buyers, and deducted from the sell price for sellers. Thus, the effective tax rate is twice the tax rate in
our model. In order not to decrease money supply in our economy, every 60 days we return tax revenues into the system as a lump sum divided among traders while maintaining the existing distribution.

### 3.3 Price clearing mechanism

Market clearing price $p^*$ is determined by an intersection of demand and supply curves. More specifically, the orders are sorted by price: sell orders whose price satisfies $s_v \leq p^*$ from lowest to highest, and buy orders whose price satisfies $b_u \geq p^*$ from highest to lowest. These buy and sell orders are then matched from the bottom of the list while there is at least one pair to be matched. Thus the last (buy or sell) order may be satisfied only partially. Variables $a_i$ and $c_i$ are updated accordingly.

### 3.4 Simulation procedure

The artificial financial market described above is used for extensive Monte Carlo simulations. The market is populated with 800 traders evenly divided into four groups: random, fundamentalist, momentarian, and contrarian. Initial wealth of agent $i$ both in cash and stocks is set as follows: Traders are divided into groups of 20 and within each group initial cash $c_i(0)$ is distributed according to Zipf's law with parameter 1 and mean of 50000. Number of each agent’s assets $a_i(0)$ averages at 1000 in all cases.

After fixing the tax rate, agents begin to interact according to their respective decision rules. Every simulation run is composed of 3600 trading sessions, or trading days, which corresponds to 15 years. First 5 years of market operations are then considered as an initialization period and those data are not taken into account. Every simulation run is then repeated 300 times for each tax rate. The tax rate is varied from 0% to 3% in 0.05 percentage point increments.

At the end of every trading day of each simulation, we collect the information on the market price of the traded asset, daily traded volumes, as well as the characteristics of the four different trader types. As a result, for every level of the Tobin tax we obtain 3000 trading years worth of data. This sample is large enough for robust statistical inference.

### 4 Results

#### 4.1 Aggregate market data

First, we focus on the analysis of the price time series and traded volumes as a function of the Tobin tax, as decrease in liquidity is allegedly one of the main costs of FTTs.

Figure 1 depicts the relationship between traded volumes and the tax rate. The results clearly show that traded volume is not a monotonic function of the tax rate but rather is maximized around the tax rate of 0.15%, which corresponds to 0.3% overall tax rate.\(^\text{10}\) This result is counterintuitive, therefore...

\(^{10}\)Recall that the tax is imposed on both sides of the transaction.
let us turn our attention to Figure 2, where we analyze the response of the supply and demand to the imposed tax rate. The demand for assets is highly fluctuating with a moderately decreasing trend. On the other hand, the supply of assets initially drops with an introduction of the Tobin tax and then consequently decreases with the tax rate. The supply for assets is less volatile compared to the demand and the relation between the supply and the tax rate is more robust. The results therefore show that the relative decrease in the supply of assets leads to an increase in trade volumes.

Figure 1: Volumes traded

Figure 2: Demanded and supplied volumes.

The liquidity is, however, only one argument in the Tobin tax debate, so let us now analyze returns to better understand the effect of FTTs on risk. Graphs of the first four central moments and median of the daily log-returns in Figure 3 show two important results. First, standard deviation of returns goes up (which is similar to the results of Mannaro et al., 2008). Second, and more importantly, skewness and kurtosis decrease in absolute value, making the distribution more “normal”. While there is no significant
correlation between mean of returns and tax rate, median rises with higher tax rate. The increase in normality is also supported by weekly and monthly returns (results available upon request).

Figure 3: Moments of returns as a function of the tax for daily log-returns

The basic analysis of log-returns therefore suggests that the deviation of the price process from normality is decreasing with the increasing tax rate. Standard deviation of returns goes up, which corresponds to Case E in Table 1. However, we still need to analyze the relative contribution of price jumps to assess the impact on volatility.

4.2 Quadratic variation vs. integrated variation

We use the daily frequency and calculate the relative contribution of price jumps to the total variance provided in Eq. (13). The left panel of Figure 4 shows the quadratic variation as estimated by the realized variance $\hat{RV}_{Daily}$ in daily levels.

The figure suggests an increase in volatility due to the imposed tax. However, for very low values of the tax rate, we see that there is a decrease in volatility, therefore we may conclude that a relatively small tax rate decreases overall volatility of the markets. This observation holds for weekly and monthly returns as well.

Right panel of Figure 4 depicts the ratio $\hat{JS}_{Daily,T}(\tau)$—the relative contribution of the price jumps to the quadratic variation. The picture clearly shows that the contribution of price jumps to the overall
variance steadily decreases as the tax rate grows. Since our price process fluctuates around the fair price, which is fixed, the $\hat{JS}_{Weekly,T}(\tau)$ and $\hat{JS}_{Monthly,T}(\tau)$ are closer to each other and the effect of the diminishing price jump contribution to the overall quadratic variation is not significant.

In summary, the Tobin tax increases the overall quadratic variation of prices, while decreasing the contribution of price jumps. This corresponds to case (C,E) in Table 1. The increasing tax rate therefore makes prices more volatile and more Gaussian. This can be interpreted as a trade-off between increase in quadratic variance and decrease in number of price jumps and non-normality. This intuition is in line with decreasing kurtosis and increasing variance in Figure 3.

In the following text, we explore the rate of price jump arrivals in greater detail. We employ the test statistics in (9) with 95% confidence interval and identify price jumps in the entire sample for each tax rate. The size of sample is 3000 trading years, which gives 720,000 observations of daily prices. In addition to overall price jumps, we also study upward and downward jumps separately.

Figure 5 depicts the number of identified price jumps as a function of the tax rate. The rate of overall price jump arrivals decreases with increasing tax rate and the decrease is convex. The subsequent figures for upward and downward price jumps show that the convexity comes from the upward price jumps, which suggests a saturation of the price jump arrivals around 2.5% tax rate. On the other hand, the number downward price jumps is decaying in a linear way and there is no hint of the saturation effect. In conclusion, the tax rate lowers the number of price jump arrivals, and this effect is more pronounced in the case of downward price jumps.

The regression line seen in the figures comes from an empirical model capturing the relationship between the number of price jumps and the tax rate:

$$N_\tau = \alpha_1 + \alpha_2 \tau + \alpha_3 \tau^2 + \epsilon_{\tau}. \tag{21}$$

Table 2 summarizes the results of the estimation. We perform regression for overall number of price jumps. \footnote{Again, recall that the effective tax rate is double.}

Table 2

<table>
<thead>
<tr>
<th>Tobin tax (%)</th>
<th>Overall (\hat{JS})</th>
<th>Upward (\hat{JS})</th>
<th>Downward (\hat{JS})</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.06</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>0.2</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
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<tr>
<td>0.3</td>
<td>0.07</td>
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<td>0.07</td>
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<tr>
<td>0.4</td>
<td>0.075</td>
<td>0.075</td>
<td>0.075</td>
</tr>
<tr>
<td>0.5</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Figure 4: Realized Variance $\hat{RV}_{Daily}$ and ratio $\hat{JS}_{Daily,T}(\tau)$ in daily levels
Figure 5: Number of jumps – one-day returns

(a) Overall

(b) Upward jumps

(c) Downward jumps
jump arrivals as well as separately for arrivals of upward and downward jumps. The estimated coefficients support the visual inspection of the graphs, where in particular $\alpha_3$ for upward price jumps is significantly higher than $\alpha_3$ for the downward price jumps. Further, the figures show that price jumps represents 6.8% percents of all returns, which drops to 6.4% at highest considered tax rate. Weekly and monthly returns exhibit similar pattern.

Table 2: Relationship between tax rate and number of jumps for daily returns.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Overall N</th>
<th>Upward N</th>
<th>Downward N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax rate</td>
<td>-17.08***</td>
<td>-9.357***</td>
<td>-7.720***</td>
</tr>
<tr>
<td></td>
<td>(0.980)</td>
<td>(0.667)</td>
<td>(0.934)</td>
</tr>
<tr>
<td>Tax rate sq.</td>
<td>0.0197***</td>
<td>0.0170***</td>
<td>0.00260</td>
</tr>
<tr>
<td></td>
<td>(0.00316)</td>
<td>(0.00215)</td>
<td>(0.00301)</td>
</tr>
<tr>
<td>Constant</td>
<td>49,105***</td>
<td>18,595***</td>
<td>30,510***</td>
</tr>
<tr>
<td></td>
<td>(63.60)</td>
<td>(43.30)</td>
<td>(60.58)</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>61</td>
<td>61</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.973</td>
<td>0.922</td>
<td>0.937</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3 Risk of portfolio – TVaR

We calculate the risk of the portfolio composed of our artificial asset over a period of time using the TVaR measure defined in (11). The change in the tax rate affect the TVaR through two channels. The first channel is the quadratic variation, which increases as the tax rate grows, causing the TVaR to increase. The second channel works in the opposite direction — the decrease in the rate of price jumps caused by the increased tax rate lowers the TVaR. Thus, the final response of the TVaR will be a combination of these two opposing effects.

Figures 6 show the TVaR for maturities ranging from the short term to the long term. We use 6 horizons to maturity: 1 day, 1 week, 1 month, 1 quarter, 10 years, and 15 years. For every investment horizon, we compute the TVaR for $p = 0.001$, $p = 0.01$, and $p = 0.05$. In all these cases, the TVaR is a decreasing function of the imposed tax rate. This means that losses projected with our measure and in any investment horizon considered in this analysis are increasing with the increasing tax rate. We can therefore conclude that from the TVaR perspective, the variance is growing faster than the price jumps are decreasing and therefore an investor tends to suffer higher losses due to the imposed Tobin tax.

---

12This follows from the fact that for a fixed $p$-level and fixed quadratic variation, adding one large price jump to the very left tail of the distribution will lower the (negative) TVaR, while the $p$-th quantile will increase.
Figure 6: Tail value at risk

(a) 1-day losses

(b) 5-day losses

(c) 20-day losses

(d) 60-day losses

(e) 10-year losses

(f) 15-year losses
4.4 Market microstructure

To determine what exactly drives these results we now turn our attention to the market micro-structure of our artificial market. More precisely, we focus on changes in the aggregate behavior of the four trading groups caused by the variation in the tax rate. Figure 7 reports the average daily inventories—assets and cash—for the four groups as a function of the Tobin tax. For random and momentarian traders, an increase in the tax rate has a negative effect on both asset and money stocks. These two groups are therefore directly negatively affected by the imposed tax. Contrarians experience an initial increase in the asset stocks as the tax rate is imposed, but the positive trend is eventually overturned and the inventory starts decreasing with the tax rate. In the case of money stocks, the average amount of money held is steeply decreasing with increasing tax rate. Finally, fundamentalist traders benefit from the growing Tobin tax. The amount of money they hold is positively affected by the tax rate, while the average amount of assets responds negatively to an initial increase in the Tobin tax, however this trend is reversed as the tax rate goes up. This evidence suggests that Tobin tax rate affects fundamentalists’ and contrarians’ asset stocks in the opposite way.

The effect of the tax on the price process and the rate of price jumps is directly connected to liquidity of the market. Figure 8 reports the daily averages of the supply and demand of the assets by the traders group. The amount of assets that each of the four groups of traders is willing to supply is negatively affected by the Tobin tax, although there are some differences in the response to lower tax rates between fundamentalists and the other three groups.

On the other hand, the demand has a different response to the tax for different groups. The demand by random traders is highly volatile while only mildly negatively affected by the imposed tax. The demand by momentarian and contrarian traders is a decreasing function of the tax for the most part, but these two groups differ in the response to very small tax rates. Fundamentalists, on the other hand, demand more assets as the tax increases. The marginal effect of the tax is most prominent for low tax rates. The response of fundamentalists and the contrarians goes in the opposite direction.

Figure 9 shows us the results of the interaction of supply and demand. It reports the average amount of assets sold and purchased by individual traders. The pattern of response to the imposed Tobin tax is similar in all four groups. First, there is an increase in the activity when a low tax rate is imposed. Afterwards, the amount of realized trades is decreasing with increasing tax rate. The marginal effects of small tax rates are different between the groups, though.

To analyze traders’ behavior more rigorously, we extend the model (21) and include some additional information about the traders’ group behavior. First, the only exogenous variable in our model is the Tobin tax and therefore including other variables in the system would lead to a possible endogeneity. The reason why to include these endogenous variables is to reflect the fact that the different traders’ group respond to the imposed tax in a very non-linear way, as was documented above. To explain the
Figure 7: Inventories by traders

(a) Assets

<table>
<thead>
<tr>
<th>Tobin tax (%)</th>
<th>Assets held by R</th>
<th>Average no. of assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>60000</td>
<td>5000</td>
</tr>
<tr>
<td>1.0</td>
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<td>6000</td>
</tr>
<tr>
<td>2.0</td>
<td>80000</td>
<td>7000</td>
</tr>
<tr>
<td>3.0</td>
<td>90000</td>
<td>8000</td>
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</table>

<table>
<thead>
<tr>
<th>Tobin tax (%)</th>
<th>Assets held by F</th>
<th>Average no. of assets</th>
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<tbody>
<tr>
<td>0</td>
<td>620000</td>
<td>5500</td>
</tr>
<tr>
<td>1.0</td>
<td>660000</td>
<td>6500</td>
</tr>
<tr>
<td>2.0</td>
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<td>7500</td>
</tr>
<tr>
<td>3.0</td>
<td>750000</td>
<td>8500</td>
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<table>
<thead>
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<th>Tobin tax (%)</th>
<th>Assets held by T</th>
<th>Average no. of assets</th>
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<tbody>
<tr>
<td>0</td>
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<td>5500</td>
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</table>

<table>
<thead>
<tr>
<th>Tobin tax (%)</th>
<th>Assets held by C</th>
<th>Average no. of assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>60000</td>
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<tr>
<td>1.0</td>
<td>70000</td>
<td>6500</td>
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<td>3.0</td>
<td>90000</td>
<td>8500</td>
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</table>

(b) Cash

<table>
<thead>
<tr>
<th>Tobin tax (%)</th>
<th>Cash held by R</th>
<th>Average cash held (Th's)</th>
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<tr>
<td>0</td>
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<td>3.0</td>
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<th>Average cash held (Th's)</th>
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<tr>
<td>0</td>
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<td>1.0</td>
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<td>3.0</td>
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<th>Tobin tax (%)</th>
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<th>Average am. of money (Th's)</th>
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</thead>
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<td>6500</td>
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<td>3.0</td>
<td>12000</td>
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<th>Cash held by C</th>
<th>Average am. of money (Th's)</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>5500</td>
<td>5500</td>
</tr>
<tr>
<td>1.0</td>
<td>6000</td>
<td>6000</td>
</tr>
<tr>
<td>2.0</td>
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<td>6500</td>
</tr>
<tr>
<td>3.0</td>
<td>7000</td>
<td>7000</td>
</tr>
</tbody>
</table>
Figure 8: Market order book by traders

(a) Supply

(b) Demand
Figure 9: Market activity by traders

(a) Sold assets

(b) Purchased assets
non-linear behavior, we should include higher order polynomials in the tax rate. The same we may expect in the case of the overall price jump figures. An alternative to the inclusion of higher order polynomials is a regression of the amount of price jumps on the highly non-linear but endogenous functions of the tax rate—the properties of the different traders’ groups. We therefore estimate the following model:

\[ N_{\tau} = \alpha_1 + \alpha_2 \tau + \alpha_3 \tau^2 + \sum_{i=R,T,F,C} \alpha_i^{(i)} s^{(i)} + \sum_{i=R,T,F,C} \alpha_5^{(i)} d^{(i)} + \epsilon_{\tau}, \quad (22) \]

where \( s^{(i)} = S^{(i)} / \sum_{i=R,T,F,C} S^{(i)} \) is a share of assets sold by group \( i \) with \( S^{(i)} \) being the average volumes of assets sold by group \( i \) every trading day, and \( d^{(i)} = D^{(i)} / \sum_{i=R,T,F,C} D^{(i)} \) the share of demanded assets, where \( D^{(i)} \) is the average volumes of assets demanded by group \( i \) every trading day. These effects of market liquidity on price jump frequency are of particular interest. Table 3 summarizes the results of the estimation. Since we use relative shares, only three of the four groups are present in the regression to avoid collinearity, since by construction 1 = \( s^{(F)} + s^{(T)} + s^{(R)} + s^{(C)} \) and 1 = \( d^{(F)} + d^{(T)} + d^{(R)} + d^{(C)} \).

First, the results of the full specification suggest that the number of price jumps up is not significantly affected by any of the variables. However, the large errors also suggest a specification problem, possibly collinearity (or already mentioned endogeneity). On the other hand, the total number of price jumps and the number of downward price jumps share the same dependence on the Tobin tax and on the amount of assets sold by trend followers. When we restrict the model and only include demand, we see that the relative demand by the fundamentalists play a crucial role. In particular, \( \alpha_5^{(F)} \) is significantly smaller compared to \( \alpha_5^{(i)} \)’s of the remaining groups. Since fundamentalists’ demand for assets increases with the tax, the results show that the relative demand for assets by fundamentalists is (seemingly) explaining the decrease in the number of price jumps. This result seems analogous to previous literature, where fundamentalists served a stabilizing role in the model, although this is the first time it has been shown in the context of price jumps, as opposed to Gaussian variance.

5 Conclusion

The main goal of this paper was to open discussion on the here-to-fore ignored relationship between financial transaction taxes and price jumps. We argued that looking at the effect of FTTs on realized variance as a measure of volatility is insufficient, as it does not convey enough information. Our point was that an increase in variance itself does not necessarily mean less stable markets, because realized variance can be decomposed into two parts – Gaussian variance and price jumps. As we have shown, the variance may go up through an increase in Gaussian variance, while the contribution of price jumps may go down, decreasing the kurtosis of the return distribution. This result seems to be driven by different responses of individual trader types to the tax. More precisely, relative weight of fundamentalists in our model is an increasing function of the tax rate. Given that there is a sizeable literature on hedging
Table 3: The effects of the tax rate and average shares of sold volumes by traders group on the number of jumps for daily returns.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>-1.499**</td>
<td>-1.641***</td>
<td>142.3</td>
<td>-1.446***</td>
<td>-919.9***</td>
<td>-526.0***</td>
<td>-1.636**</td>
<td>-1.679***</td>
<td>42.83</td>
</tr>
<tr>
<td>( \tau )</td>
<td>-1,499*</td>
<td>-1,641***</td>
<td>142.3</td>
<td>-1,446***</td>
<td>-919.9***</td>
<td>-526.0***</td>
<td>-1,636**</td>
<td>-1,679***</td>
<td>42.83</td>
</tr>
<tr>
<td>( \tau^2 )</td>
<td>137.7</td>
<td>128.0*</td>
<td>9.694</td>
<td>207.5***</td>
<td>106.1***</td>
<td>101.3***</td>
<td>120.0</td>
<td>101.7</td>
<td>18.27</td>
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<td>( s(R) )</td>
<td>12,059</td>
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<td>-49,767</td>
<td>5,122</td>
<td>46,237</td>
<td>41,116</td>
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<td></td>
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<tr>
<td>( s(T) )</td>
<td>145,187**</td>
<td>137,828***</td>
<td>7,359</td>
<td>190,180**</td>
<td>179,742***</td>
<td>10,438</td>
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<td>( s(C) )</td>
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<td>104,540*</td>
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<td>108,989*</td>
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<td>-12,404</td>
<td>-10,958</td>
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<td>( d(F) )</td>
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<td>-999.3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( d(T) )</td>
<td>806,657***</td>
<td>560,658*</td>
<td>254,999</td>
<td>-509,949</td>
<td>-502,313</td>
<td>-7,636</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>21,722</td>
<td>35,425</td>
<td>57,147</td>
<td>39,175***</td>
<td>17,938***</td>
<td>21,237***</td>
<td>32,126</td>
<td>-18,959</td>
<td>51,085</td>
</tr>
<tr>
<td>Observations</td>
<td>61</td>
<td>61</td>
<td>61</td>
<td>61</td>
<td>61</td>
<td>61</td>
<td>61</td>
<td>61</td>
<td>61</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.979</td>
<td>0.970</td>
<td>0.948</td>
<td>0.977</td>
<td>0.966</td>
<td>0.946</td>
<td>0.979</td>
<td>0.971</td>
<td>0.949</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
against Gaussian variance, this result implies that such a tax may improve efficiency of these formulas, and through that, functioning of markets. We believe that our work opens up interesting avenues for further research on the relationship between FTTs and price jumps. More precisely we aim to apply the model in the empirical setup and test the hypotheses implied by this model using the asset prices data. Moreover, as Mannaro et al. (2008) themselves argue, more a model with more sophisticated, possibly risk averse, agents may provide different results, serving as a robustness check.

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References


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