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

Hynek Lavička
Tomáš Lichard
Jan Novotný

CERGE EI

Charles University
Center for Economic Research and Graduate Education
Academy of Sciences of the Czech Republic
Economics Institute

WORKING PAPER SERIES (ISSN 1211-3298)
Electronic Version

511

Working Paper Series 511
(ISSN 1211-3298)

Sand in the Wheels or Wheels in the Sand? Tobin Taxes and Market Crashes

Hynek Lavička
Tomáš Lichard
Jan Novotný

CERGE-EI
Prague, March 2014

ISBN 978-80-7343-315-4 (Univerzita Karlova. Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-308-5 (Akademie věd České republiky. Národohospodářský ústav)

Sand in the Wheels or Wheels in the Sand? Tobin Taxes and Market Crashes*

Hynek Lavička[1], Tomáš Lichard[2], and Jan Novotný[2,3]

[1]FNSPE, Czech Technical University, Prague, Czech Republic

[2]CERGE-EI, Prague, Czech Republic†

[3]Cass Business School, City University London, UK

Abstract

The 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 a 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. However, the results are not robust to the size of the artificial market as non-linearities emerge when the size of the market is increased.

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

JEL Classification Number: C15, C16, C61, G17, G18, H23

†CERGE-EI is a joint workplace of the Center for Economic Research and Graduate Education, Charles University in Prague, and the Economics Institute of the ASCR, v. v. i. Address: CERGE-EI, P.O. Box 882, Politických vězňů 7, Prague 1, 111 21, Czech Republic

*We wish to express our thanks to Aleš Černý, Filip Matějka, Jens Perch Nielsen, Riccardo Pianeti, Sergey Slobodyan, Stanley Zin, and seminar participants at Cass Business School and CERGE-EI for their valuable comments and discussion. The usual disclaimer applies. All three authors are grateful to the GACR grant No. P402/12/2255 for their material and financial support and RVO68407700 of the Czech Ministry of Education for support and development of Sunrise cluster where calculations were executed. TL and JN gratefully acknowledge the GAUK grant No. 586112. JN acknowledges funding from the European Community's Seventh Framework Program FP7-PEOPLE-2011-IEF under grant agreement number PIEF-GA-2011-302098 (Price Jump Dynamics).

Abstrakt

Současná krize oživila zájem o daň z finančních transakcí (DFT) jako způsobu omezení negativních externalit na finančních trzích. Bohužel, současný výzkum na poli finančních trhů nepřináší dostatečně hluboký náhled na dopad zavedení daně z finančních transakcí na fungování trhů, neboť se současná literatura zaměřuje příliš úzce na gaussovskou varianci jakožto míru volatility. V tomto článku ukazujeme nezbytnost studování vztahu mezi cenovými skoky, Gaussovskou variancí a DFT. Zatímco gaussovská variance nemusí být sama o sobě problém, ne-normalita distribuce výnosů způsobená cenovými skoky negativně ovlivňuje nejen výkonnost zajišťovacích algoritmů, ale je přímo spjata s frekvencí katastrofických událostí na trzích. Abychom pochopili výše uvedené vztahy, používáme model finančních trhů založený na multiagentním přístupu. Výsledky ukazují, že regulátor je při nastavování optimální daně postaven před volbu mezi nízkou celkovou volatilitou a nízkým počtem cenových skoků. Analýza dále ukazuje, že výsledky závisí na velikosti trhu, neboť pro větší trhy se zvětšuje nelinearita v odezvě systému na DFT.

1 Introduction

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" (p.154). He and his co-authors offered more arguments in favor of the tax in Eichengreen, Tobin, and Wyplosz (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 the merits of Tobin-like taxes has not so far reached a definite conclusion. The proponents of the tax claim that an 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 the long-run equilibrium. Although recently the debate has been gaining new traction in political circles, it is often driven more by ideology and politics rather than rigorous academic research. The academic debate has been 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 are so far mixed.

The arguments against the tax are often based on the efficient market hypothesis (EMH from now on; see Fama, 1965), which implies speculators cannot destabilize market, as rational arbitrageurs would trade against them and drive prices towards their fundamental level. However, as De Long, Shleifer, Summers, and Waldmann (1990) first showed in an early study, this result is not robust to the choice of arbitrageurs' risk aversion and length of their trading horizon as more risk averse rational traders may not be willing to trade against noise traders. Another argument against FTTs claims 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 the microeconomic behavior of the financial market agents. 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, 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 a model with fundamentalist and chartist traders in foreign exchange markets. In this model, a low tax rate first crowds out chartism, but higher rates lead to misalignment due to a decreasing number of fundamentalists. Using a different approach, Mathevet and Steiner (2012) show in a dynamic global game that in an 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 the tax 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 the 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 a significant amount of trading activity moved to London. However, it must be noted that the Swedish transaction tax of one percent (later increased to two percent) was higher[1] than what Tobin proposed originally (0.5 percent), 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, Chowdhry, and Yan (2003) examined the effect of transaction costs in general on volatility (defined as the standard deviation of prices) in foreign exchange rates for four different currencies and found a 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 led to higher volatility, implying a negative correlation between transaction costs and volatility. Finally, a third group of literature has not found any significant effect—see e.g. Hu (1998), who studied the effects of stock transaction tax on market volatility and turnover taking advantage of 14 tax changes that occurred in the stock markets of Hong Kong, Japan, South Korea, and Taiwan during the period 1975-1994.

We see two major issues that are left rather unexplored. First, a scale effect arguably plays a major role (Tobin tax was meant to be a global tax). Small markets like Sweden does not have a significant impact on the world economy, so if 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 studies have ignored a significant source of information by focusing on conditional variance as a single measure of volatility. Concerning the first point, some work has already been 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. a fundamentalist vs. chartist). The 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 in the other. The opposite effect of transaction tax on volatility in a two-market framework was obtained by Mannaro, Marchesi, and

[1]Note although the tax rate was initially 0.5 percent and later increased to one percent, this tax was nominally borne by both sides of the transaction implying the overall tax rate of one percent and two percent, respectively.

Setzu (2008), who used the methodology of agent-based models (ABMs). They used four types of traders with different strategies, who can trade in a maximum of two markets. However the relative share of strategies is kept fixed exogenously, but agents may choose where to trade and whether to trade at all. On the other hand, one of the few more recent studies, Bianconi, Galla, Marsili, and Pin (2009), concluded that a 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, Laurent, & Petitjean, 2010) that the volatility of most financial instruments can be decomposed into two parts: a regular Gaussian component and a price jump component. Many models that aim to estimate conditional variance, such as various GARCH models[2], 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. A 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 the 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 a 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

[2]For an overview see Hamilton (1994).

jumps. As Andersen, Benzoni, and Lund (2002) and Andersen, Bollerslev, and Diebold (2007) show, price jumps are present in the majority of price time series; therefore, their presence should be the subject of research. Price jumps can have a serious adverse impact on the predictive power of pricing formulae and on the 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 & Mykland, 2008 or Lahaye, Laurent, & Neely, 2011) considers new information a primary source of price jumps, while other authors, like Joulin, Lefevre, Grunberg, and Bouchaud (2008) and Bouchaud, Kockelkoren, and Potters (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. For analyzing the two latter views, the ABM methodology is especially appropriate since it allows for the 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 a simulation of the artificial financial markets in Section 2. Furthermore, in Subsection 2.2, we model the impact of the FTT on the price process and provide estimators to quantify this effect. Section 3 discusses the results of our analysis. We discuss the importance of the results and avenues for further research in Section 4.

2 Modeling financial markets with transaction tax

This section introduces the framework to model the financial transaction tax in financial markets and its impact on the distribution of log-returns with a special focus on extreme

[3]For illustrations of changes in the pricing formulae caused by price jumps see Pan (2002) or Broadie and Jain (2008). Brooks, Černý, and Miffre (2011) discuss the effect of higher moments on optimal allocations within a utility-based framework.

price movements. We use the agent-based computational model by Raberto, Cincotti, Focardi, and Marchesi (2003) and Mannaro et al. (2008). Their modeling framework replicates the stylized facts of the financial returns and therefore, in the subsequent part, we implement recent understanding from the financial econometrics to assess properly the response of the extreme price movements to the FTT.

2.1 The agent-based model

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

1. They allow for the explicit modeling of said transactions (interactions);
2. They allow for the modeling of each agent independently.

Thus explicitly modeled micro interactions lead to the emergence of macro properties (bottom-up approach). Our basic model is based on the methodology of Raberto et al. (2003) and Mannaro et al. (2008), who present an agent-based model of artificial ex ante heterogeneous traders, which leads to the price dynamics of financial assets satisfying the well-known stylized facts of clustering volatility, non-zero skewness, and higher kurtosis, or price jumps. In particular, we consider four types of agents based on their behavior: random traders, fundamentalist traders, momentum traders, and contrarian traders. We use the parameters calibrated by Raberto et al. (2003) and Mannaro et al. (2008) so that the price series generated match the usual stylized facts of financial markets. It is worth pointing out out that the four types of trading agents can be related to various types of institutional traders in the market ranging from noise retail traders to sophisticated hedge funds. To illustrate, the momentum traders can be a representation of the real-world marginal retail investors following the moving averages as well as the large algo funds, who employ advanced algorithms to capture the emergence of trend channels.

The agent-based modeling procedure itself is performed as follows (analogously to Lavička, Lin, & Novotný, 2010): We set initial conditions of the model including the number of interacting agents and various model-specific parameters described below. Then, we let the economy evolve step by step until a pre-determined number of steps (or trading days) is reached. At every step, we record the closing price, the overall traded amount of assets, the 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 the tax revenue.

In our specification, we assume that every agent acting in the markets is working in the same time scale. This means that every agent has the same computational and trading ability to react to the price movements. We stress this fact by denoting every such moment as a trading day. However, it is important to keep in mind that this is for presentation purposes only and every such step could be called a trading millisecond, which would seemingly mimic the "continuous-time" operations of current financial markets.

Finally, we assume fixed strategies for all the agents throughout the paper. This means that an agent cannot change the strategy as time passes based on the performance of such strategy. The reason for this assumptions is three-fold. First, we want to observe the effect of the introduction of the FTT on the immediate markets. Keeping the same proportion of traders with different trading strategies allows us to understand the different pressure caused by the FTT on different trading strategies. Second, trading agents usually stick to one strategy and do not switch often. For instance, the macro hedge fund is not very likely to switch its trading strategy to high-frequency algorithmic trading as it would be too costly, and it would send a misleading signal to potential investors. This does not mean that such a fund will not evolve; however, the development will rather be in the form of improvements to macro research and in experimentation with different macro models. Finally, the different agents with different strategies may represent the different parts of one legal entity. The professional trader will usually try a set of strategies and keep an independent track of them as it would be convenient for back-testing and risk management. Similarly, a large investment bank will have as its subsidiaries different hedge funds that will explore different strategies. These hedge funds will have independent accounting and will very likely be independent legal entities. As the agents differ in their wealth and all the trading strategies are proportional to the trading wealth, our model covers all of the above cases.

2.1.1 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, an agent i is characterized by her cash holdings ($c_i(t)$) and asset holdings ($a_i(t)$), in addition to the strategy she follows.

Random traders Random traders (denoted as R) do not follow any particular strategy—with equal probability they issue a buy or a sell order. They are a proxy for traders that trade for their private reasons independent of the market situation, or who follow noisy information. Such a type of trader may include those who need to hedge their positions, institutional investors, or long-term traders who aim to trade over a horizon exceeding any horizon considered in this study.

If random traders buy (sell), the limit price of their buy (sell) order is determined as:

$$l_i^b = p(t) \cdot X \, , \tag{1}$$

$$l_i^s = \frac{p(t)}{X} \, , \tag{2}$$

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

$$s_i = k \cdot \sigma_i(\omega_i) \, , \tag{3}$$

where $\sigma_i(\omega_i)$ is the standard deviation of the log-returns computed based on window length following uniform distribution $\omega_i \sim U[2, 5]$. Parameter k is set to 1.9. As Mannaro et al. (2008) argue, the dependence on past variance simulates a GARCH-type memory. 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.

The traded amount is random and determined as follows:

$$
\begin{aligned}
q_i^b &= U_{\mathbb{N}}\left(0, \left\lfloor c_i\left(t\right)/l_i^b\right\rfloor\right) , &(4)\\
q_i^s &= U\left(0, a_i\left(t\right)\right) , &(5)
\end{aligned}
$$

where $\left\lfloor c_i\left(t\right)/l_i^b\right\rfloor$ is an integer-valued quantity denoting the maximum amount of stocks the trader is able to buy for the price l_i^b with $\lfloor X \rfloor$ denoting the highest integer smaller than X and $U_{\mathbb{N}}\left(i, j\right)$ being an integer-valued uniform distribution, which draws integers between i and j, inclusively.

Fundamentalist traders Fundamentalist traders (F) base their decisions on their beliefs about the fundamental price of assets. Such traders are assumed to be endowed with enough faculty to process all available information ranging from macro-economic fundamentals to accounting variables. As a consequence, they have perfect knowledge of the fundamental price and try to arbitrage the difference between the current price and the fundamental price as they know the system is mean reverting towards the fundamental price. Such traders include macro hedge funds or traders who closely follow particular companies/sectors.

If a fundamentalist trader i decides to buy or sell, he buys/sells the following amount of assets

$$
\begin{aligned}
q_i^b &= \min\left(\left\lfloor \frac{c_i\left(t\right)}{p_f}\right\rfloor, \left\lfloor k \cdot \frac{\left|p\left(t\right) - p_f\right|}{p_f} \cdot \frac{c_i\left(t\right)}{p_f}\right\rfloor\right) , &(6)\\
q_i^s &= \min\left(a_i\left(t\right), \left\lfloor k \cdot \frac{\left|p\left(t\right) - p_f\right|}{p_f} \cdot a_i\left(t\right)\right\rfloor\right) , &(7)
\end{aligned}
$$

which depends on the current $(p\left(t\right))$ and the fundamental (p_f) price of the asset, with parameter k being the same as in the random traders' case. In effect, these traders are arbitrageurs who try to take advantage of the differences between market and fundamental price of assets.

Momentum traders Momentum traders—denoted as T—follow trends. They buy when the price goes up and sell when it goes down. Momentum trading strategies are still popular among investors, and this type of trader, thus, represents algorithmic hedge funds, whose algorithms predict the continuation of the trend, or, for instance, retail traders who bet on the combination of the signals involving moving averages and thus fully rely on technical analysis. Momentum traders can also contribute to the building up of bubbles as their behavior is inherently based on herding and involves positive feedback.

Each momentum trader is assumed to look back at the history based on an idiosyncratic time window ω_i, which is randomly drawn from a normal distribution as $\omega_i \sim U[3, 20]$ at the beginning of the simulation. This setup mimics the wide variety of trading strategies. If a momentum trader i decides to issue an order, the limit price l_i is computed as:

$$l_i = p\left(t\right) \cdot \left[1 + k \cdot \frac{p\left(t\right) - p\left(t - \omega_i\right)}{\omega_i p\left(t - \omega_i\right)}\right], \tag{8}$$

where k is the same parameter as in previous cases. Conditional on the decision to sell (if $l_i < p\left(t\right)$) or to buy (if $l_i > p\left(t\right)$), the exact quantities are computed as follows:

$$\begin{aligned} q_i^b &= \min\left(\left\lfloor \frac{c_i\left(t\right)}{l_i} \right\rfloor, \left\lfloor \frac{c_i\left(t\right)}{l_i} \cdot u \cdot \left[1 + k \cdot \frac{\left|p\left(t\right) - p\left(t - \omega_i\right)\right|}{\omega_i p\left(t - \omega_i\right)}\right]\right\rfloor\right), & (9) \\ q_i^s &= \min\left(a_i(t), \left\lfloor a_i(t) \cdot u \cdot \left[1 + k \cdot \frac{\left|p\left(t\right) - p\left(t - \omega_i\right)\right|}{\omega_i p\left(t - \omega_i\right)}\right]\right\rfloor\right), & (10) \end{aligned}$$

where $u \sim U\left(0, 1\right)$.

Contrarian traders Similarly to momentum traders, contrarian traders (C) follow technical analysis of trends; 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. These traders benefit from the herding behavior of momentum traders. Thus, by introducing negative feedback into the market, they inadvertently lean against forming bubbles.

This implies that their behavioral rules are the same as those of momentum traders, only in the opposite direction. In particular, the decision to sell (buy) occurs if the $l_i > p(t)$ ($l_i < p(t)$), with all the other variables remaining the same.

2.1.2 Price clearing mechanism

The market clearing price p^* is determined as the intersection of the demand and supply curves. More specifically, the orders are sorted by price: sell orders whose price satisfies $s_v \leq p^*$ from the lowest to highest, and buy orders whose price satisfies $b_u \geq p^*$ from the 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. In case the last buy or sell order is satisfied only partially, p^* is determined as a weighted average of the bid and the ask price. Based on this matching, variables a_i and c_i are updated accordingly for each trader who made an exchange.

The provided model thus generates for every trading day a market price along with the volume and other market characteristics describing the profile of each of the four trading groups. In the following, we focus on the price-generating process, which by construction, satisfies the standard stylized facts known in the market, see Mannaro et al. (2008); Raberto et al. (2003).

2.1.3 Tax collection

The main goal of this paper is to analyze the impact of introding FTT on the properties—in particular, higher moments—of the price generating process. In this framework, the tax rate is imposed on both sides of the transaction. More precisely, it is added on top of the price for buyers, and subtracted from the sell price for sellers. Thus, the effective tax rate is twice the nominal tax rate in our model.

Every trade thus causes a decrease of money supply available for traders in the market, as a fraction of the turnover is collected. In order to prevent the ever-decreasing money supply, every 60 days we return tax revenues into the system as a lump sum divided among traders while maintaining the existing distribution of the money. Such a lump sum return represents both the returns on the money flows and can be also interpreted as the dividend payouts; however, the preserved money distribution constraint does not support the latter interpretation.

2.1.4 The price-generating process

The provided set of strategies offers a diverse combination of micro-based strategies, which gives rise to both sides of the trading book with a wide distribution of the demanded/supplied assets. The price clearing mechanism based on the law of supply and demand, then, implies the price-generating process, which satisfies the basic stylized facts as shown by Raberto et al. (2003) and Mannaro et al. (2008). The provided framework thus represents a natural laboratory to study the impact of financial frictions on markets and their particular impact on price dynamics. For that purpose, we introduce in the following section the standard formalism from the financial econometrics literature and focus on the dependence between price jumps of a realized price path and the amount of the imposed FTT.

2.2 Model of price process

We consider a one-dimensional asset log-price process, X, that takes the form of the Ito semi-martingale described by the following stochastic differential equation:

$$dX_t = \eta_t dt + \sigma_t dB_t + \int_{\Re} x \cdot \mu\left(dt, dx\right) \ , \tag{11}$$

where $B\left(t\right)$ is a standard Brownian motion, see Jacod and Shiryaev (1987) for an introduction in this field. Such a price model is a suitable and general candidate to model the log-price process in a realistic setup and thus tends to be appropriate in our agent-based framework, which yields a price process satisfying the stylized facts.

The spot volatility σ_t is a càdlàg process bounded away from zero almost surely. The drift η_t is, in our case, identically equal to zero[4]. Variable $\mu\left(dt, dx\right)$ is an integer-valued

[4]The fundamental price in our model is fixed, which is equivalent to a world with zero deterministic

random measure that captures a jump in X_t over a time interval $[t, t + dt)$. Thus the 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 $\int_{\Re} (x^2 \wedge 1)\, \nu_t(dx) < \infty$. 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 a corresponding jump intensity ν_t gives rise to a finite number of price jumps. More precisely, a finite number of $t_i \in [0, T]$ exists such that $U_i \equiv \Delta X_{t_i} > 0$ in the limit, with $i = 1, \ldots, N_T$. In such a case, we observe exactly N_T price jumps. The term ν_t thus affects both the U_i and the grid $\mathcal{T}_T = \{t_1, \ldots, t_{N_T}\}$, including its cardinality.

2.2.1 Financial transaction tax

The Tobin tax in the model affects the trading habits of the agents in the economy and thus the random processes in Equation(11). In particular, the process driving the Gaussian volatility and the jump measure depends on the tax rate τ:

$$\begin{array}{rl} \sigma_t \rightarrow & \sigma_t(\tau) \\ \nu_t \rightarrow & \nu_t(\tau) \end{array} . \tag{12}$$

Estimating the functional dependence between the spot processes in Equation(12) and the FTT is not a straightforward task as the randomness in the spot processes would be a confounding factor.[5] Any test would therefore require a comparison of the random processes that depend on the current state of the world. A possible solution would be to use filtering techniques to extract the latent processes $\sigma_t(\tau)$ and $\nu_t(\tau)$. Another and more intuitive solution employed in this paper is to use the integrated variables and measure the impact of the FTT over a certain time horizon on the integrated quantities. In particular, we focus on the first four moments and assess the distributional properties

interest rates. An alternative and equivalent explanation is that our model describes de-trended data. The provided framework is valid even in the case of a general CAR process with locally persistent price process at a given sampling frequency.

[5] Recall that σ_t itself is a random process with a structure similar to the log-price equation.

of the log-returns r_t as a function of the FTT. In addition, as per $\nu_t(\tau)$ measure, we estimate the number of price jumps per given sample path and analyze the impact of the FTT on the frequency of price jumps.

2.2.2 Estimating the number of price jumps

Estimating the price jump contribution to the overall quadratic variance is one way to assess the role of price jumps in the price process. Alternatively, we may directly identify the 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 the presence of a price jump in a particular return, we employ a test developed by Lee and Mykland (2008). As Hanousek, Kočenda, and Novotný (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 Eq.(11). The test statistic is based on the results of the 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 statistic developed by Lee and Mykland (2008) is defined as:

$$\frac{\max_{t\in A_n} |\mathcal{L}_t| - C_n}{S_n} \to \xi\,, \tag{13}$$

where A_n is the tested region with n observations, and $\mathcal{L}_t = r_t/\hat{\hat{\sigma}}_t$, $C_n = \frac{(2\ln n)^{1/2}}{\mu_1} - \frac{\ln\pi + \ln(\ln n)}{2\mu_1(2\ln n)^{1/2}}$, $S_n = \frac{1}{\mu_1(2\ln n)^{1/2}}$, $\mu_1 = E(|z|)$ with $z \sim N(0,1)$, and where $\hat{\hat{\sigma}}_t$ stands for the spot bipower variance defined as:

$$\hat{\hat{\sigma}}_t^2 = \frac{1}{T-1}\sum_{u=t-T+1}^{t-1} |r_u|\,|r_{u-1}|\ . \tag{14}$$

Note that the term μ_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 ξ 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.

2.3 Simulation procedure

The artificial financial market described above is used for extensive Monte Carlo simulations in a modified Zarja C++ environment for agent-based modeling developed in Lavička (2010).[6] To evaluate the robustness of the results to initial conditions, we run different specifications varying the total set of agents in the economy, the relative share of different traders, and the probability of trading p described in Section 2.1.1. A list of these specifications can be seen in Table 1.

Table 1: Simulation parameters

Population	Distribution (R:F:M:C)	p	Population	Distribution (R:F:M:C)	p	Population	Distribution (R:F:M:C)	p	Population	Distribution (R:F:M:C)	p
400	40:30:15:15	0.1	400	40:10:25:25	0.1	10,000	40:10:25:25	0.1	100,000	40:10:25:25	0.1
800	40:30:15:15	0.1	400	40:30:22:8	0.1	10,000	40:30:22:8	0.1	100,000	40:30:22:8	0.1
10,000	40:30:15:15	0.01	400	40:30:8:22	0.1	10,000	40:30:8:22	0.1	100,000	40:30:8:22	0.1
10,000	40:30:15:15	0.05	400	20:30:25:25	0.1	10,000	20:30:25:25	0.1	100,000	20:30:25:25	0.1
10,000	40:30:15:15	0.004	400	20:50:15:15	0.1	10,000	20:50:15:15	0.1	100,000	20:50:15:15	0.1
100,000	40:30:15:15	0.1	400	40:50:05:05	0.1	10,000	40:50:05:05	0.1	100,000	40:50:05:05	0.1
100,000	40:30:15:15	0.05	400	60:10:15:15	0.1	10,000	60:10:15:15	0.1	100,000	60:10:15:15	0.1
100,000	40:30:15:15	0.0004	400	60:30:05:05	0.1	10,000	60:30:05:05	0.1	100,000	60:30:05:05	0.1

For all of the specifications above, the initial wealth of agent i both in cash and stocks is set as follows. First, the overall cash is divided proportionally among the trader groups. Within the trader groups, the cash is divided following the Zipf law. After fixing the tax rate, which remains the same for a given specification, agents begin to interact according to their respective decision rules. Every simulation run is composed of 3,600 trading sessions, or trading days, which corresponds to 15 years. The first five years of market operations are then considered as the initialization period, and those data are not taken into account. Every simulation run is then repeated 200 times for each tax rate. The tax rate is varied from zero to three percent in 0.05 percentage point increments.

At the end of every trading day of each simulation, we collect the following data: the

[6] Downloadable from `http://sourceforge.net/projects/politeconomy/`.

market price of the traded asset, the daily traded volumes, and the behavior and wealth (both in terms of assets and cash) of the different trader types. As a result, for every level of the Tobin tax, we obtain 200 samples of 10 trading years worth of daily data. This sample is large enough for robust statistical inferences.

3 Results

This section reports the results of a baseline model with 400 traders and a robustness check with 10,000 traders. The baseline corresponds to the specifications used in previous studies and thus directly extends the existing literature. The robustness check allows us to determine if there is any nonlinear scale effect that would interact with the effect of the Tobin tax. The results for other specifications presented in Table 1 are available upon request; however, their qualitative nature supports the findings reported in this section.

3.1 A market with 400 traders

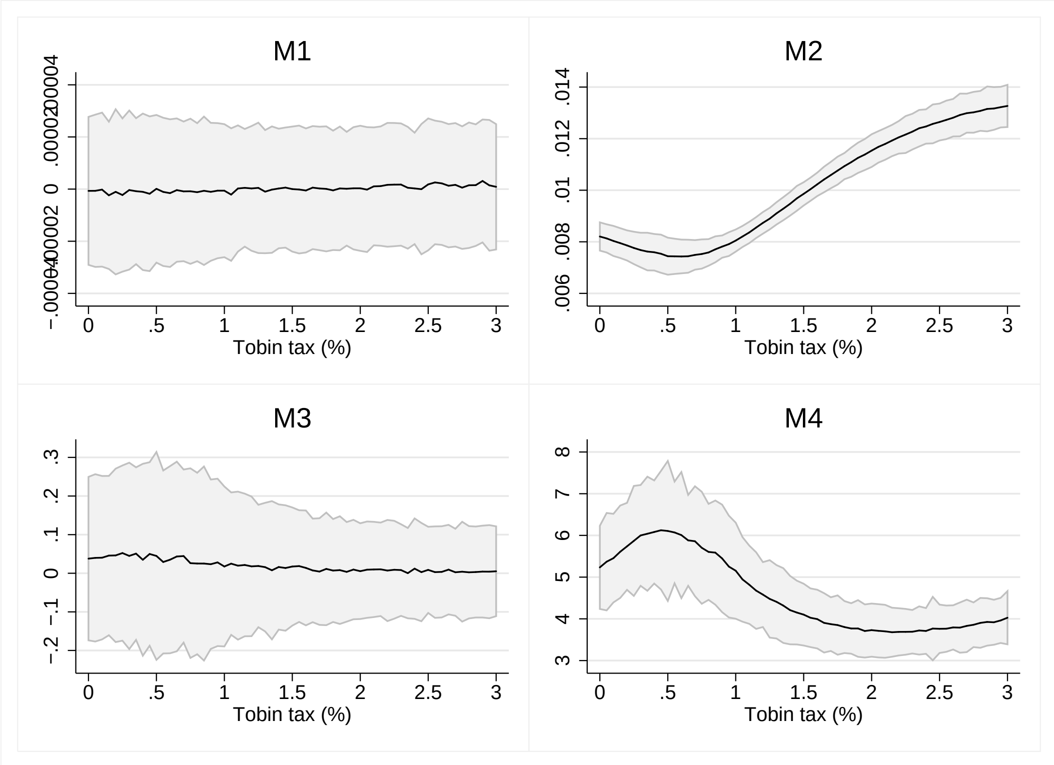
In this subsection, we report the results of a simulation with 400 traders, distributed into four trader groups described in Section 2.1.1. More precisely, our baseline market consists of 40 percent of random traders, 30 percent of fundamentalist traders, and 30 percent of chartists (divided evenly between trend followers and contrarians).

3.1.1 Price Behavior

Figure 1 shows the first four moments of the distribution of log-returns with 95 percent confidence bands. It is evident from the figures that the tax has an insignificant effect on the mean and skewness of the distribution. A comparison of variance and kurtosis shows that at low levels a rise in the tax has a negative effect on variance but increases kurtosis. From approximately a 0.5 percent tax, the trend is reversed—variance goes up but kurtosis decreases, making the distribution more Gaussian, albeit with a higher standard deviation.

Figure 2 depicts the first, fifth, 95th, and 99th percentiles of the return distribution.

Figure 1: The first four moments of the log-return distribution for $N = 400$

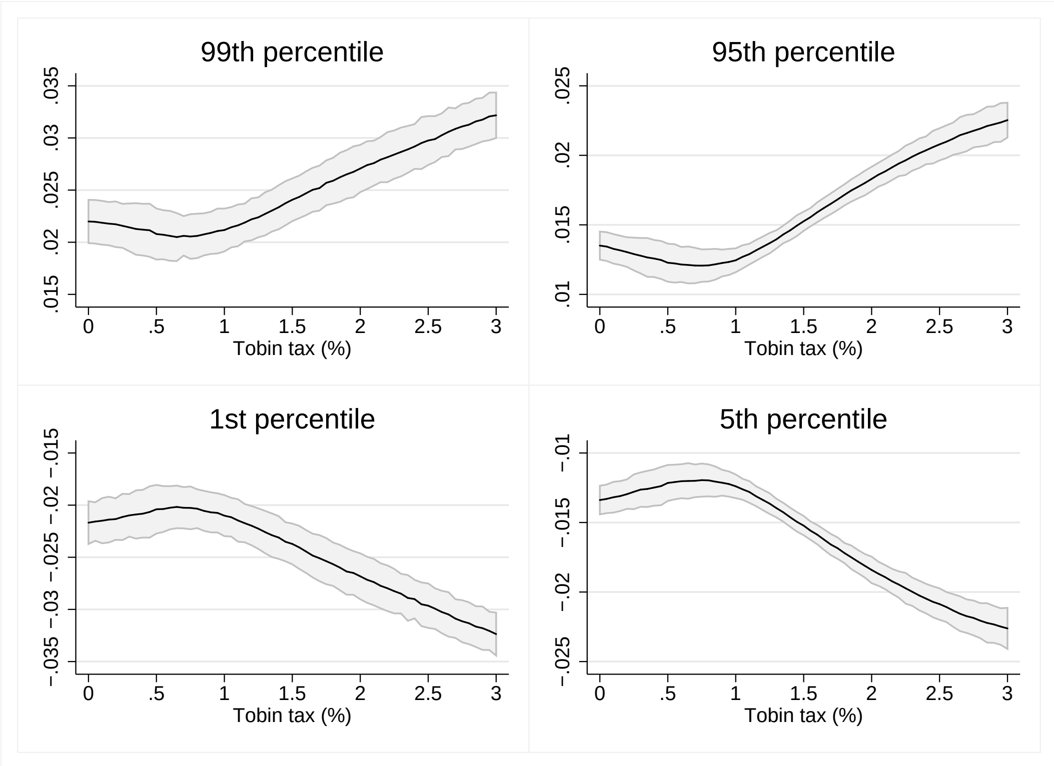


Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Clearly, the distribution of returns widens as the second moments suggest. The role of the fourth moments, in particular the suppression of heavy tails, partially compensates for the widening of the distribution. However, the percentile analysis does not fully capture the interplay between the second and fourth moments. This, in turn, corresponds to a well-accepted inability of the standard percentile based VaR measures to efficiently deal with extreme price movements.

In conclusion, a plain comparison of the first four moments supports the well-accepted belief of market practitioners that FTT will increase the market volatility. This is usually interpreted as a bad signal when markets lose their depth. However, figures also show that the fourth moment—the proxy for fat tails—decreases after reaching certain critical value (around the tax rate of 0.5 percent). This can make the story which considers the volatility and the FTT more intricate. Such a pattern suggests that FTT makes the returns less fat-tailed and thus eliminates black-swan events. In the following sections, we focus more in detail on extreme events and answer the question whether the decrease in black-swan events caused by the Tobin tax really offsets the cost of higher Gaussian

Figure 2: Percentiles for $N = 400$



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

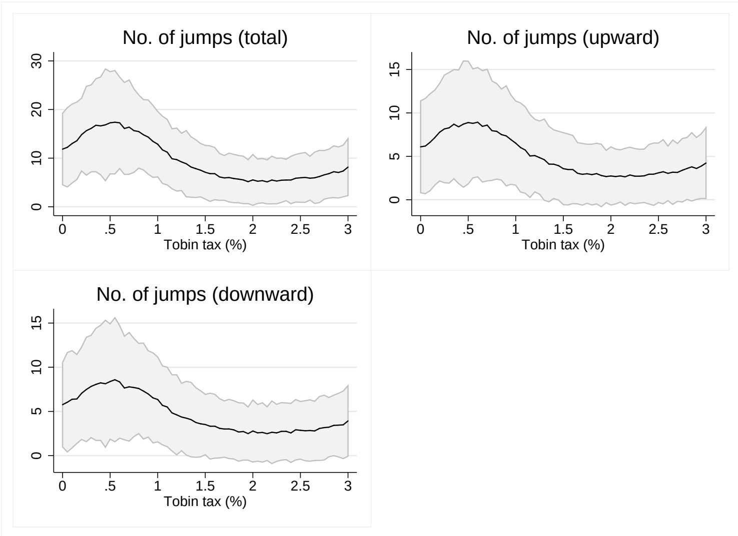
volatility.

3.1.2 Jump statistics

In the following text, we explore the rate of price jump arrivals in greater detail as neither momentum-based tools nor percentile analysis can properly assess the role of extreme returns. We employ the test statistics in Equation (13) with a 95 percent confidence interval and identify price jumps in the entire sample for each tax rate. In addition to overall price jumps, we also study upward and downward jumps separately.

Figure 3 depicts the number of identified price jumps as a function of the tax rate. The rate of overall, upward and downward price jump arrivals increases with an increasing tax rate at first, and this increase reaches the maximum at 0.5 percent tax. In conclusion, in order to decrease the number of price jumps, the tax rate in the model has to be higher than approximately one percent. This intuition is in line with the pattern exhibited by variance and kurtosis in Figure 1. In addition, the figures also suggest that increasing the tax rate beyond two percent may have an adverse effect as the number of price jump arrivals tend to slightly increase though due to the error bars, this effect is not statistically significant.

Figure 3: Number of jumps for $N = 400$



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

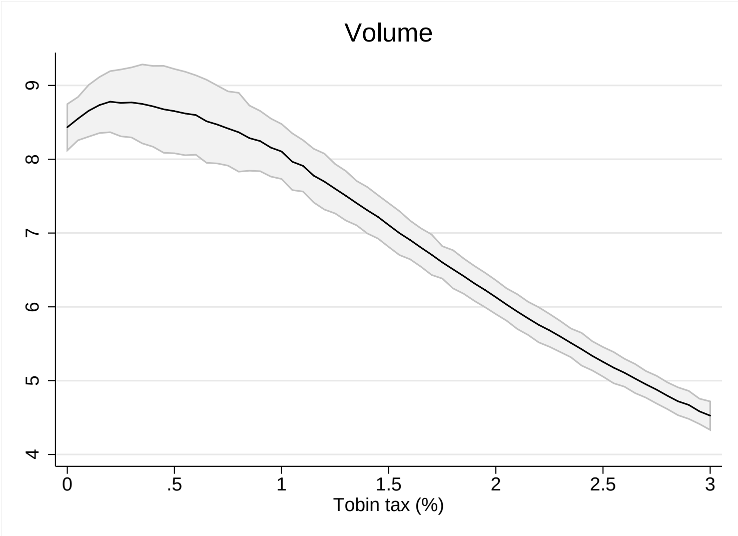
3.1.3 Aggregate market data

In this part, we focus on the aggregate market data other than the price process, which was discussed above. Namely, we analyze the amount of traded volumes as a function of the Tobin tax as decrease in liquidity is allegedly one of the main costs of FTTs.

Figure 4 depicts the relationship between traded volumes and the tax rate. The results clearly show that the traded volume is not a monotonic function of the tax rate but rather is maximized around the tax rate of 0.15 percent, which corresponds to the overall tax rate of 0.3 percent. The effect of increasing the volume after introducing a small tax rate opposes the wide-spread market intuition of a strong negative FTT impact mainly through an adverse effect on the traded liquidity. Our model shows, however, that such an effect is not necessarily the case though for larger values of the tax rate, the volume drops dramatically.

Let us turn our attention to Figure 5, where we analyze the response of the supply and demand to the imposed tax rate. Both demand and supply are monotonically decreasing with the tax rate. Therefore, the presence of slight concavity in the volume function with

Figure 4: Average trading volume for $N = 400$



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

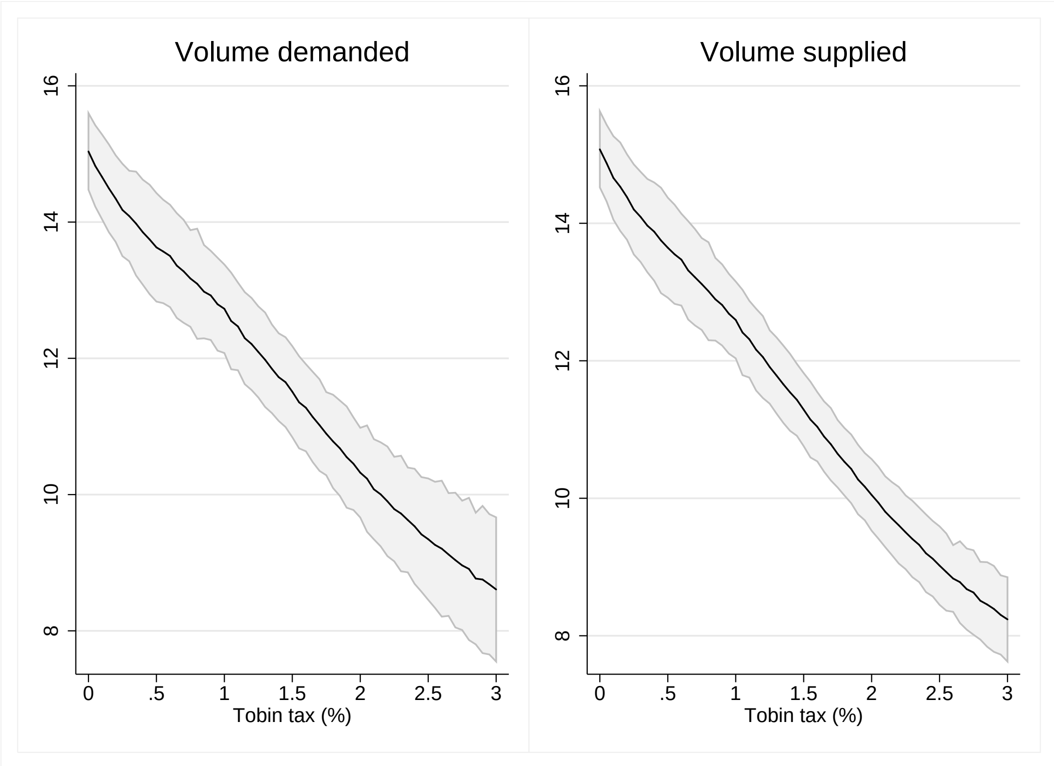
a local maxima in the traded volume occurs through the price channel. Namely, the basic intuition behind the demand and supply curve suggests that with decreasing volumes on both sides of the market, the volume of trading would decrease as well, keeping all other properties unchanged. However, that is not what we see, and therefore, the price process is thus affected by the FTT in a nonlinear way. Truly, the nonlinear response of the price process is supported by Figure 1 as discussed above.

Therefore, the effect of a small FTT on financial markets is such that it makes traders decrease, on average, the price demanded when selling assets while being able to offer a higher price when buying. Such an effect is purely a dynamic consequence of the model and cannot be derived based on the foundations of the model. It clearly stresses the fact that the interaction between agents can play a crucial role.

3.1.4 Market microstructure

To determine what exactly drives these results, we now turn our attention to the microstructure 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 6 reports the average daily inventories—assets and cash—for the four groups as a function of the Tobin tax. For random and contrarian traders, an increase in the tax rate has a

Figure 5: The average supplied and demanded volumes for $N = 400$



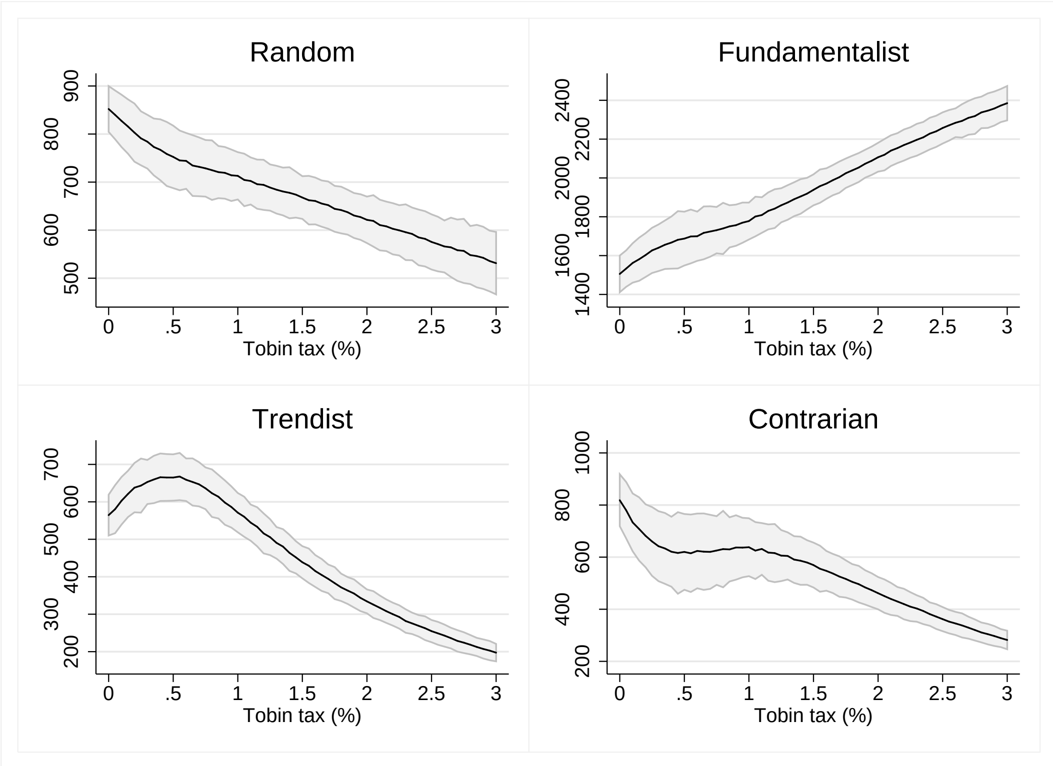
Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

negative effect on both asset and money stocks. Trendists' wealth and inventories exhibit a local maximum at around 0.5 percent tax rate. Finally, fundamentalist traders benefit from the growing Tobin tax. The amount of money and assets they hold are positively affected by the tax rate. As fundamentalists are the only traders whose trading pushes the price towards the fundamental value of the asset, the effect of the Tobin tax on the price discovery process can be interpreted as positive. In conclusion, this evidence suggests that the Tobin tax affects fundamentalists' and other traders' asset stocks in the opposite way.

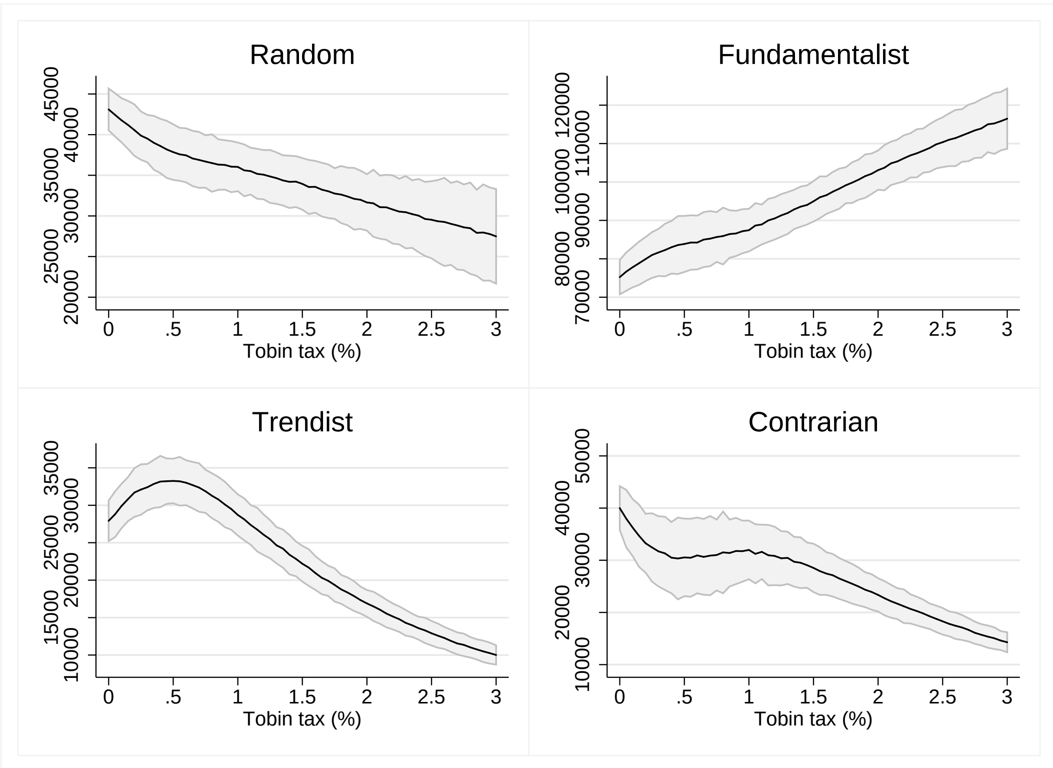
The effects of the tax on the price process and the rate of price jumps are directly connected to the liquidity of the market. Figure 7 reports the daily averages of supply and demand of the assets by the respective trader groups. Both demand and supply exhibit similar patterns. While random traders' quantities decrease almost linearly with an increase in the tax rate (the same behavior we have experienced with the aggregate demand and supply in Figure 5), the response of other trader groups is not monotonic. Fundamentalists and trendists demand more with a higher tax rate up to approximately

Figure 6: Inventories by traders for $N = 400$

(a) Assets



(b) Cash



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

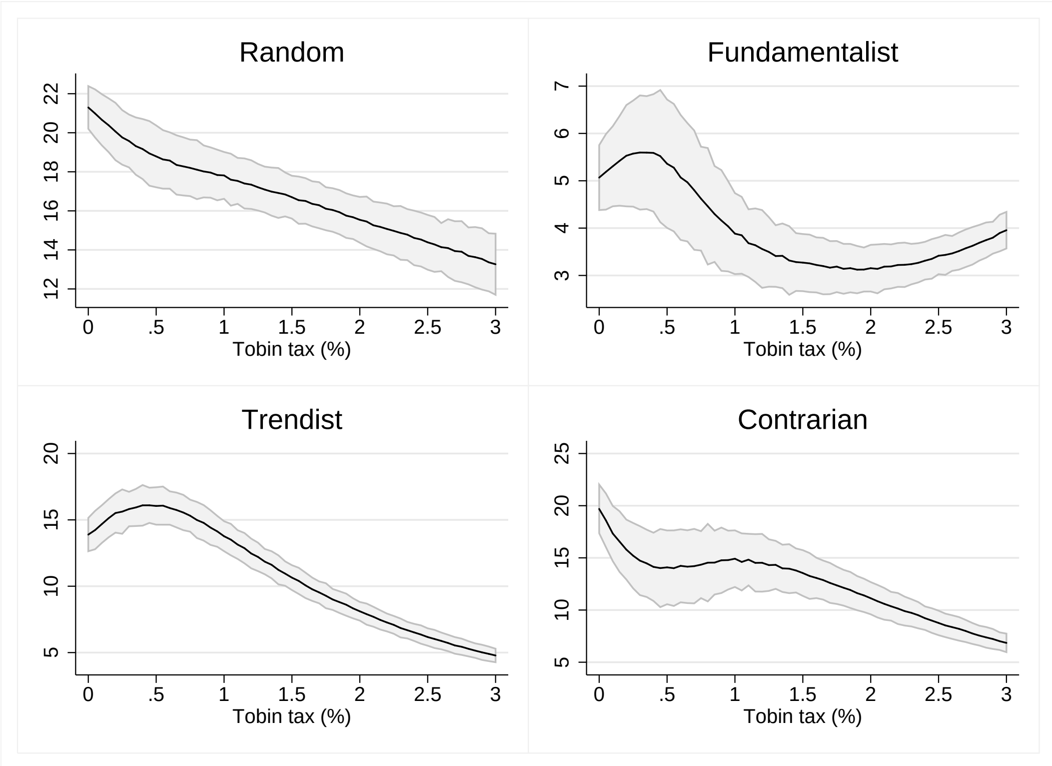
0.4 percent and then their activity decreases (although the fundamentalists' supply and demand start to go up again near 2 percent). The contrarians' response to the tax, although almost monotonically negative, is not linear. The presence of local extremum around 0.4 percent corresponds to the maximum in the aggregate traded volume in Figure 4. Therefore, the increased amount of traded assets can be in particular assigned to the increased activity of the fundamentalist and or trendist. On the other hand, the figure also suggests that the contrarians have a disruptive role in the average traded amount as they experience an inverse pattern in contrast to the two previously mentioned groups.

Figure 8 shows the results of the interaction between 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 to the supply and demand for all groups except contrarians, whose trading exhibits a hump-shaped relationship, maximized around 1.2 percent. In addition, there is a slight difference for fundamentalist traders as the amount of sold and purchased assets seem to be saturated from around the tax rate of two percent. Since the fundamentalists' demand for assets is relatively less affected by the tax (compared to random and trendist traders) and contrarian traders even increase activity up to a certain level of the tax rate, the results show that the activity of these two groups (seemingly) explains the decrease in the number of price jumps. This result seems analogous to previous literature, where fundamentalists served in aa 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.

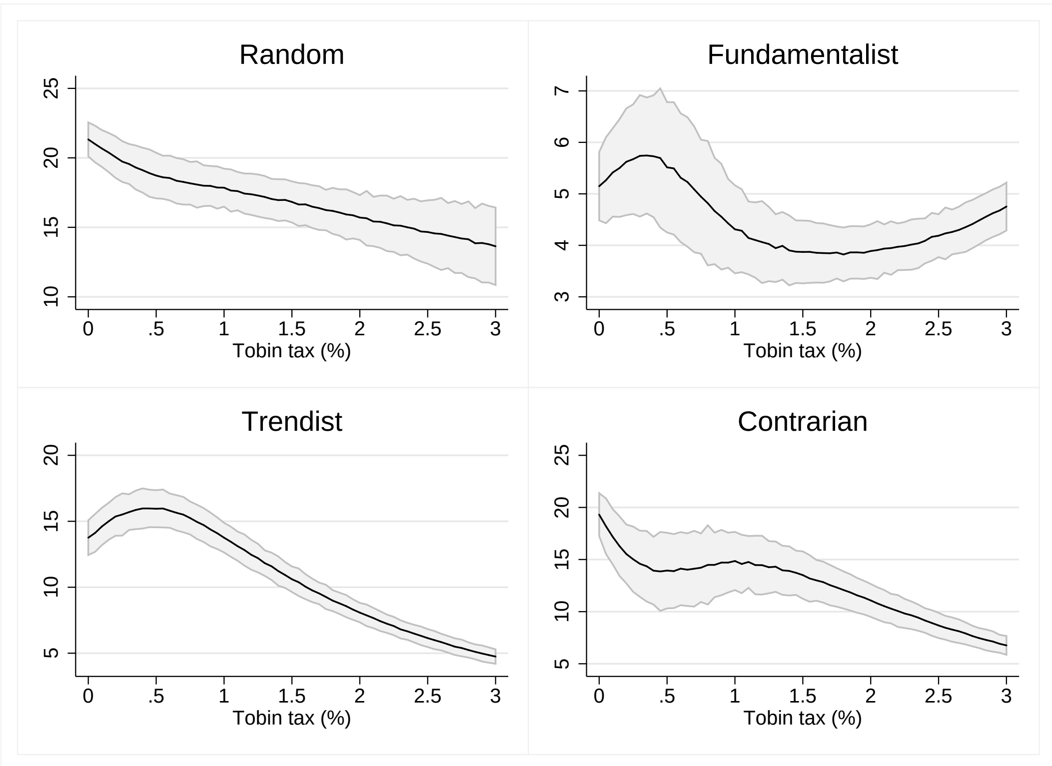
This hypothesis is supported by Figure 9 that depicts an amount of assets per trader held by every type of trading strategy in the model as a function of the tax rate. The intensity of the line color marks the level of the tax rate, with black being the zero rate and lighter shades of gray signifying higher tax rates. While traders in our model cannot choose their strategy, the relative amount of assets held by different trader groups can still be perceived as the fitness of a given strategy. The figure clearly shows that growing tax rates would make the fundamentalist strategy more attractive if the traders could choose it. The other strategies tend to decrease in fitness as the Tobin tax rises, though

Figure 7: Market order book by traders for $N = 400$

(a) Supply



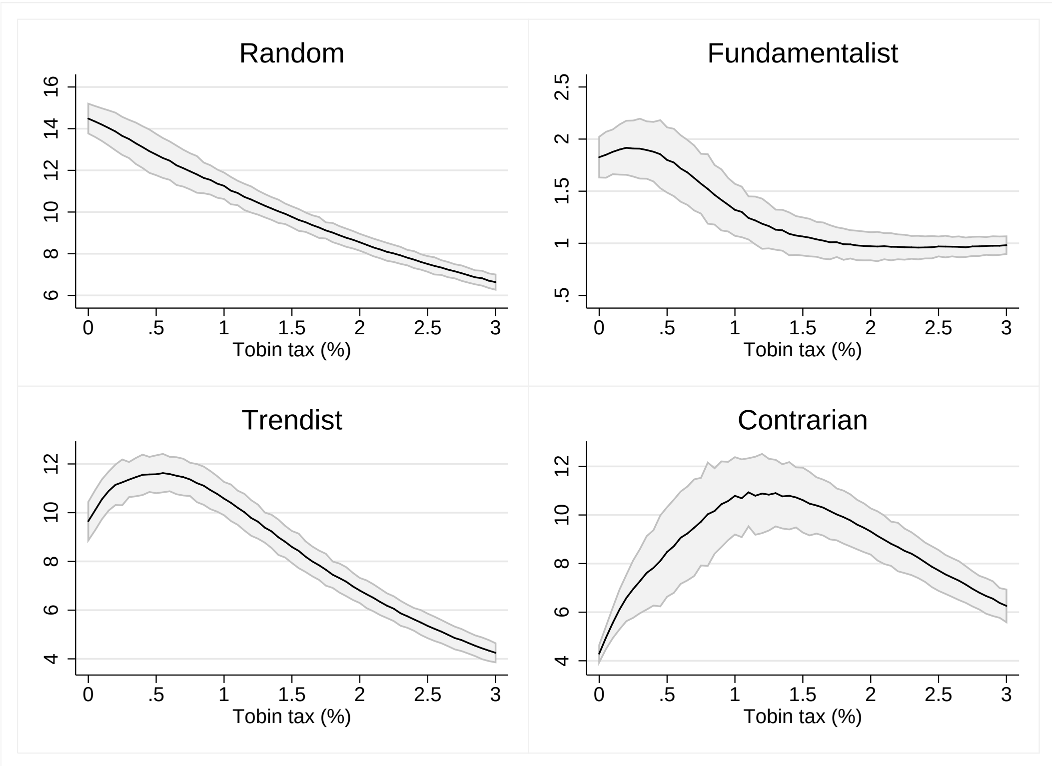
(b) Demand



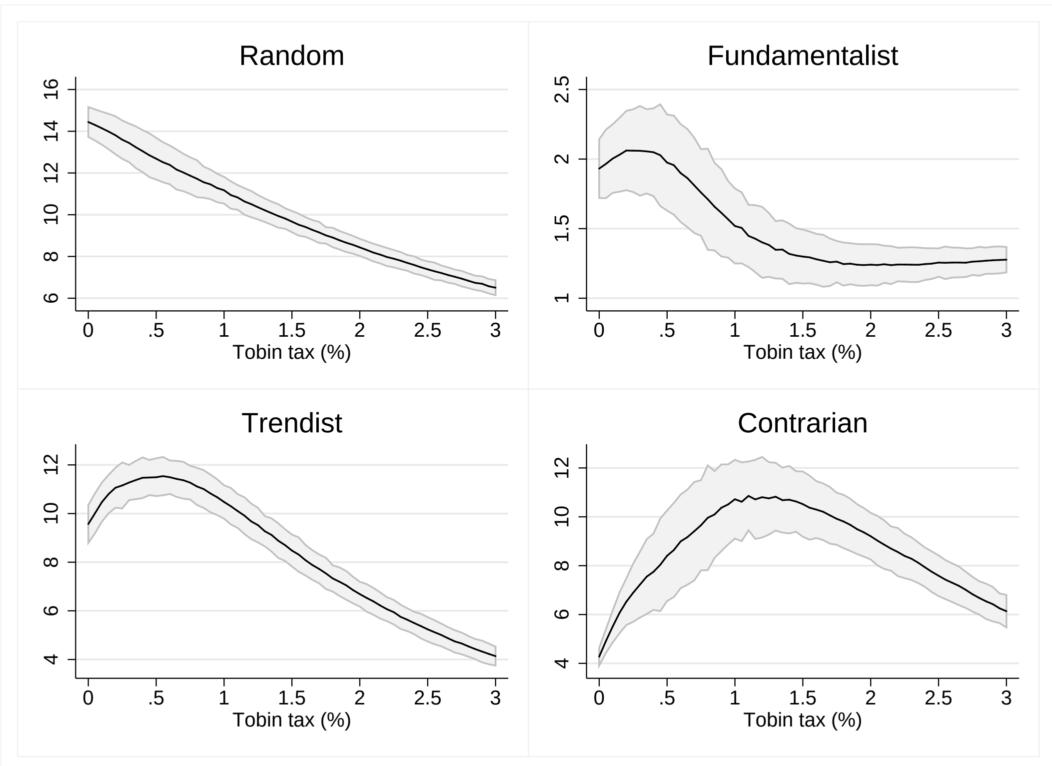
Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Figure 8: Market activity by traders for $N = 400$

(a) Sold assets



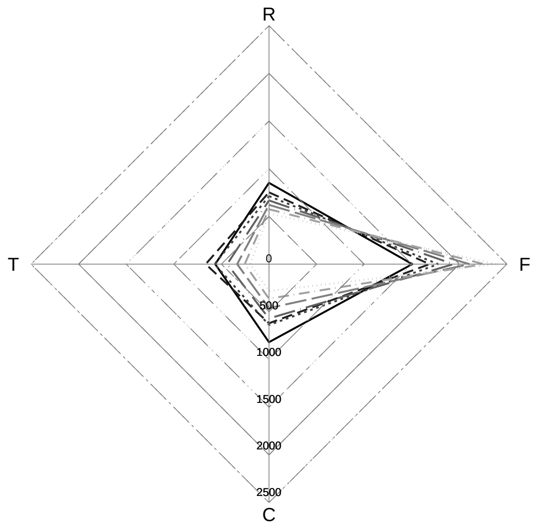
(b) Purchased assets



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

the trend is not strictly monotonous, as we can see for example at the 0.5 percent tax level and the trend follower. However, the trend follower strategy is suppressed as the tax rate rises. In addition, for the zero tax rate, we see that the trend follower is the strategy with the least amount of held assets. This suggests that the share of traders with this strategy would be decreasing in a dynamic setting.

Figure 9: Assets by trader types for $N = 400$.



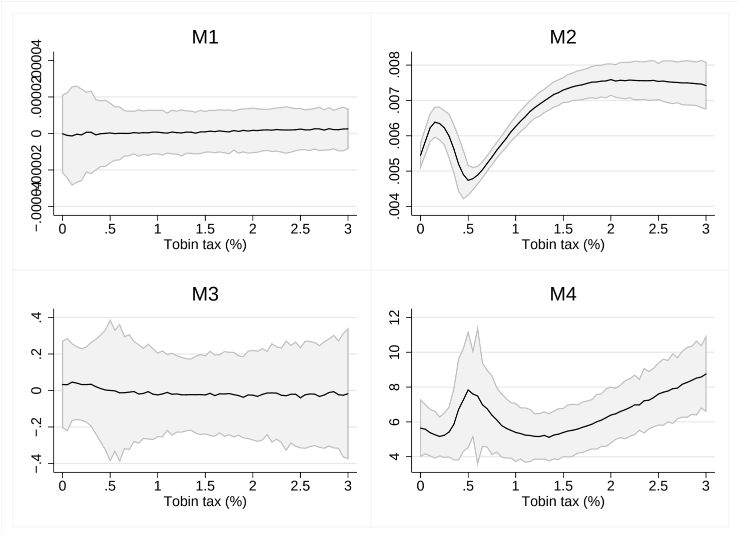
Note: The intensity of color is a decreasing function of the tax rate (black=0%).

3.2 Market with 10,000 traders – The Size Effect

To determine the effect of the market size on the results, we now report the results of a market simulation containing 10,000 traders. Their composition is the same as in the previous case. This exercise further extends study on the impact the FTT has on the financial markets towards differentiating markets of different sizes. In particular, we aim to explicitly distinguish small and large markets.

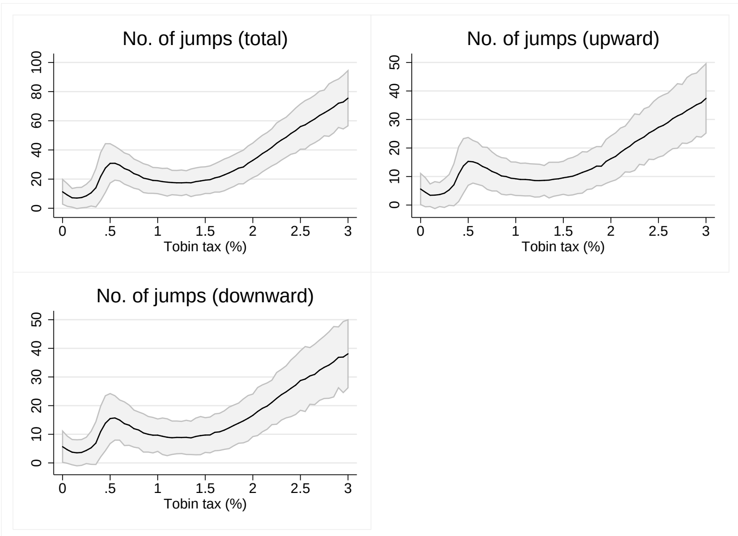
It is clear from the following figures that there is a significant increase in the size of non-linearities. Especially second and fourth moments in Figure 10 exhibit a more pronounced spike at 0.5 percent than they do in the smaller market. The number of jumps (Figure 11) exhibits a kink around 0.5 percent, and overall it goes up, rather than down, with an increasing tax rate. The rest of characteristics show a pattern similar to the one on the smaller market, only with more pronounced non-linearities (see Appendix for the rest of the figures).

Figure 10: The first four moments of the log-return distribution for $N = 10,000$



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Figure 11: Number of jumps for $N = 10,000$

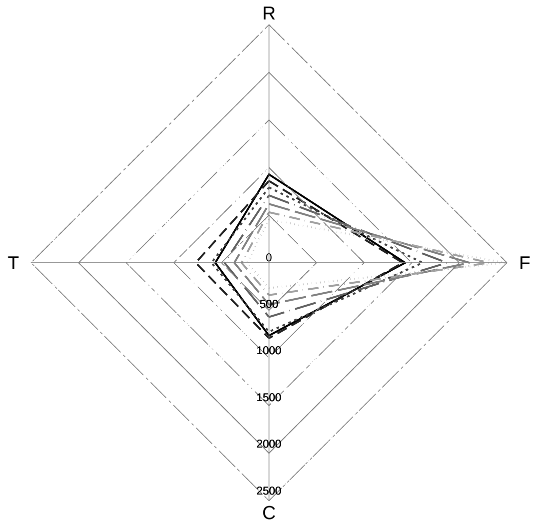


Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

When we turn to Figure 12, the evolution of strategy fitness is similar to that of the smaller market. The fitness of the fundamental strategy increases with the increasing tax rate. This is again in line with previous literature on FTTs.

In conclusion, the size effect is present in the scope of our model. In particular, we may conclude that the response of small and large financial markets to the introduction of the FTT is qualitatively similar; though, the response differs in details. Large markets

Figure 12: Assets by trader types for $N = 10,000$.



Note: The color intensity is a decreasing function of the tax rate (black=0%).

persistently show more non-linearities and therefore are more sensitive to institutional changes.

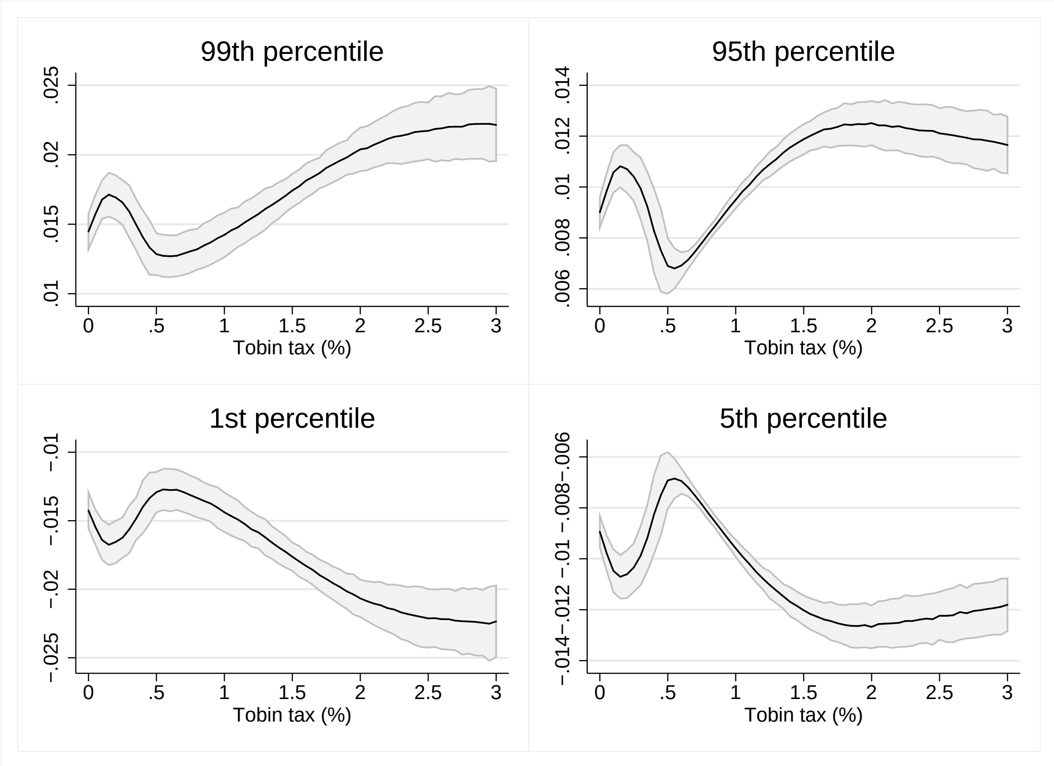
4 Conclusion

The main goal of this paper was to open the discussion on a 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 the 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, the relative weight of fundamentalists in our model is an increasing function of the tax rate.

Given that there is a sizeable literature on hedging against Gaussian variance, this result implies that such a tax may improve the efficiency of these formulae, and through this, the functioning of the markets. Our paper thus indicates that a policy maker faces a trade-off between the variance of the price process and the number of price jumps when implementing a FTT. We believe that our work opens up interesting avenues for further research about the relationship between FTTs and price jumps relevant from both an academic and a policy point of view.

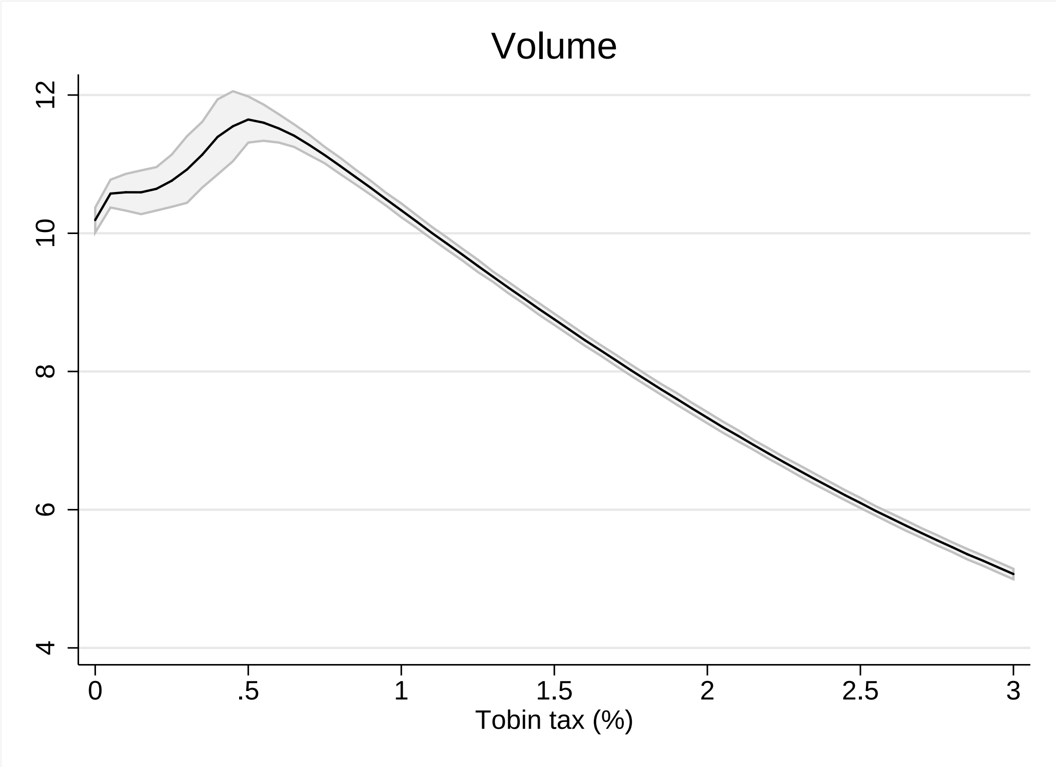
Appendix

Figure 13: Percentiles for $N = 10,000$



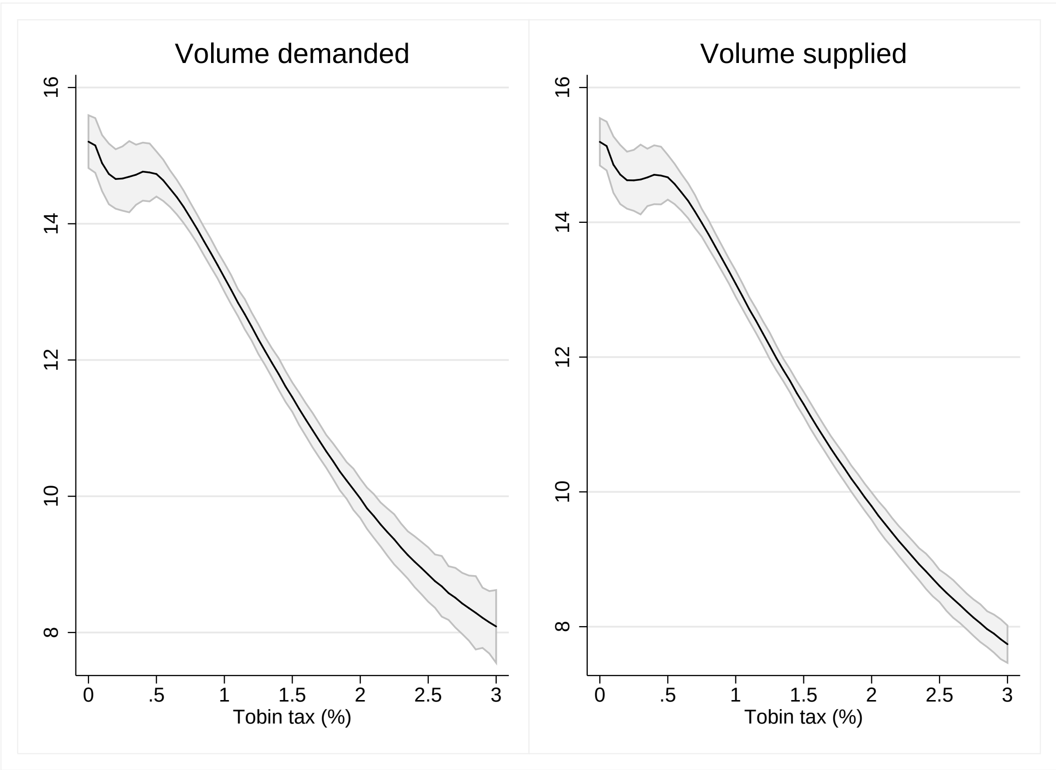
Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Figure 14: Average trading volume for $N = 10,000$



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

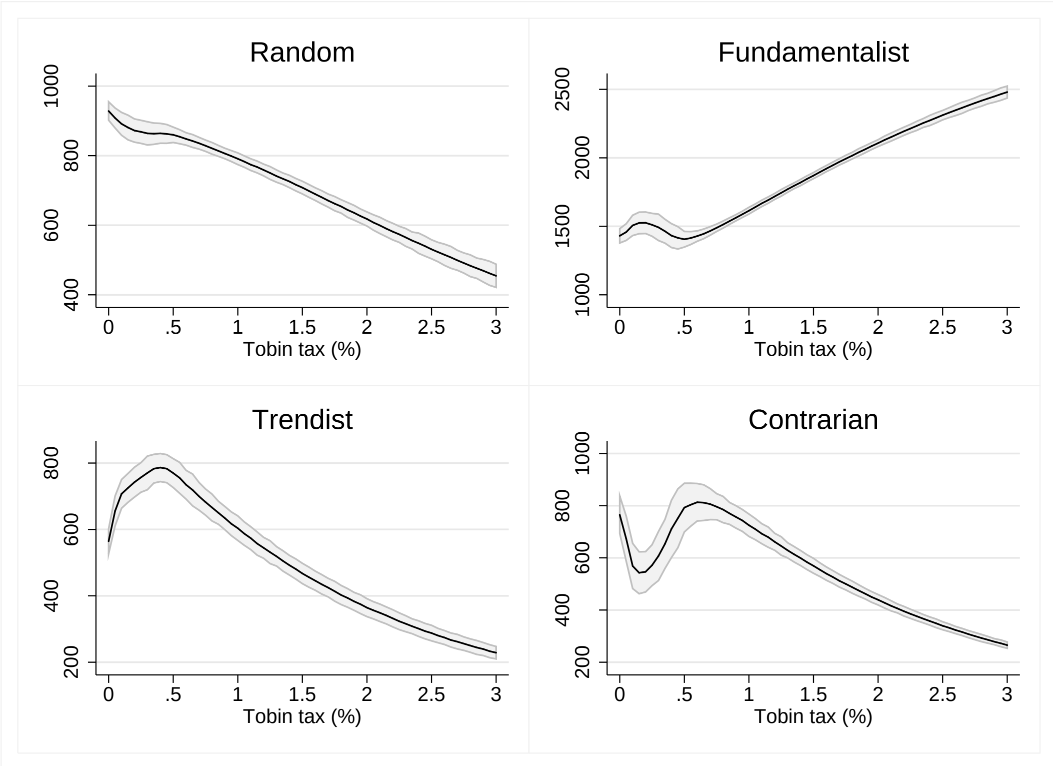
Figure 15: Average supplied and demanded volumes for $N = 10,000$



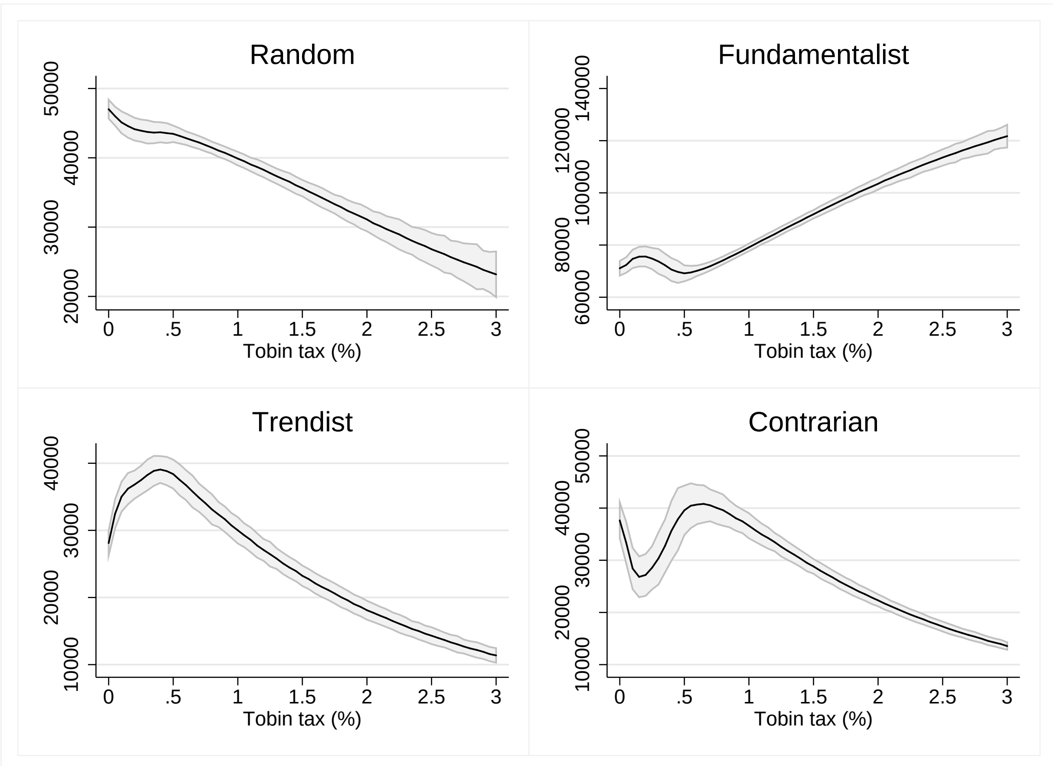
Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Figure 16: Inventories by traders for $N = 10,000$

(a) Assets



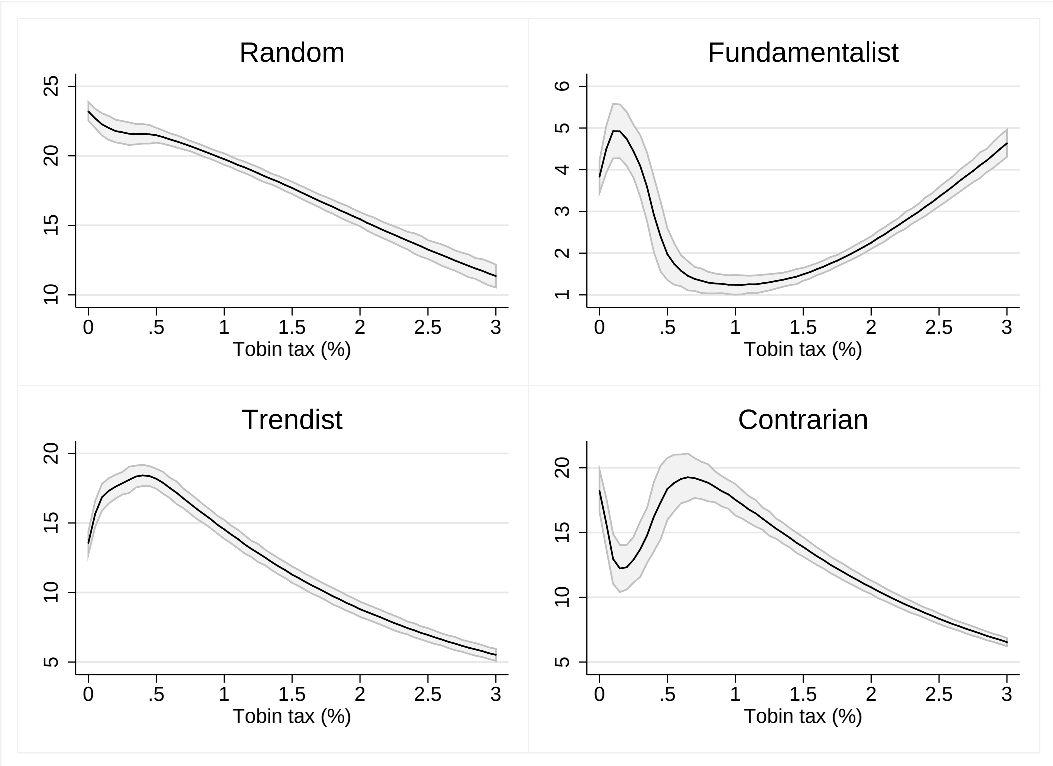
(b) Cash



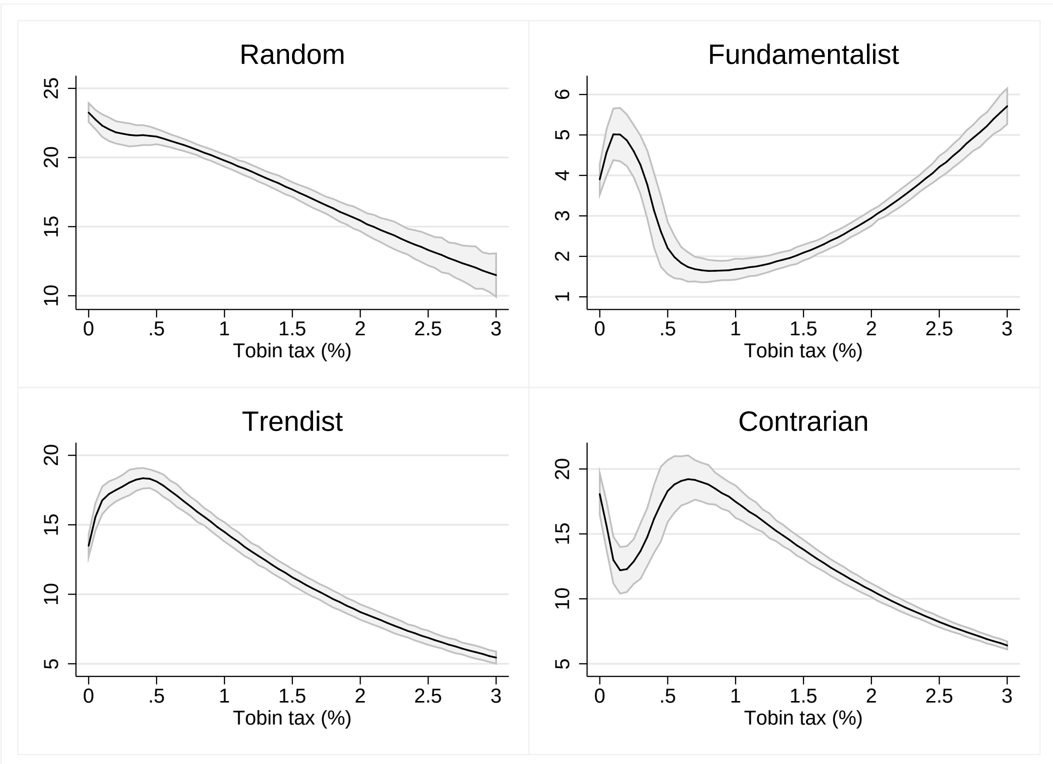
Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Figure 17: Market order book by traders for $N = 10,000$

(a) Supply



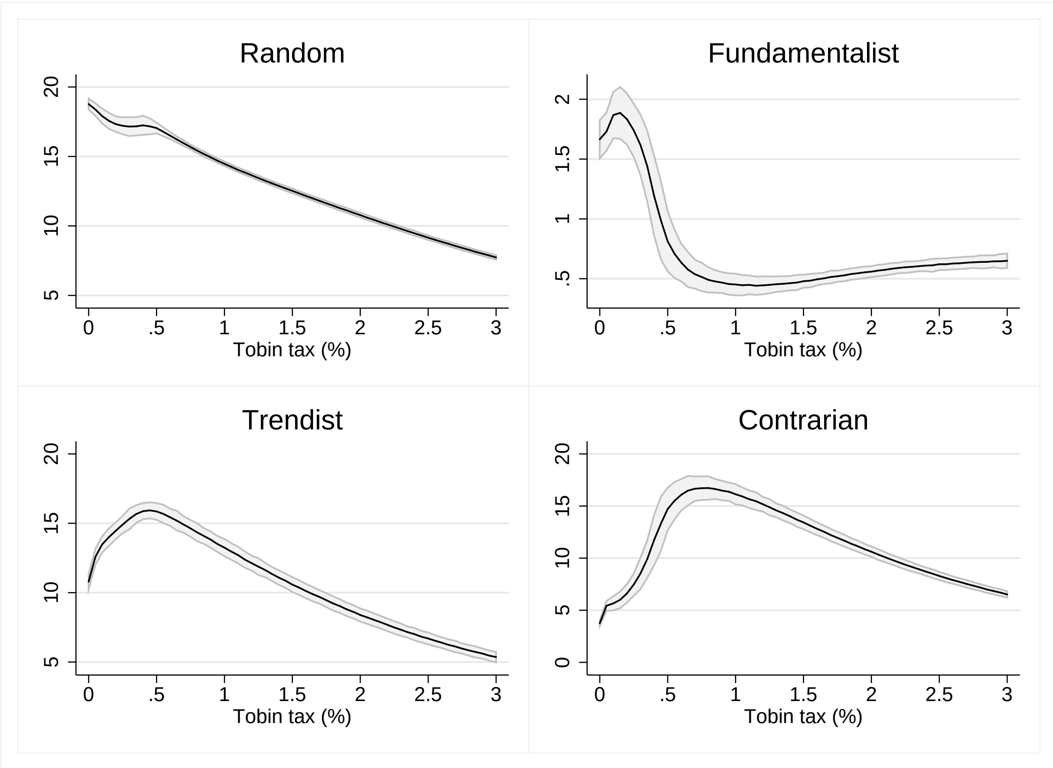
(b) Demand



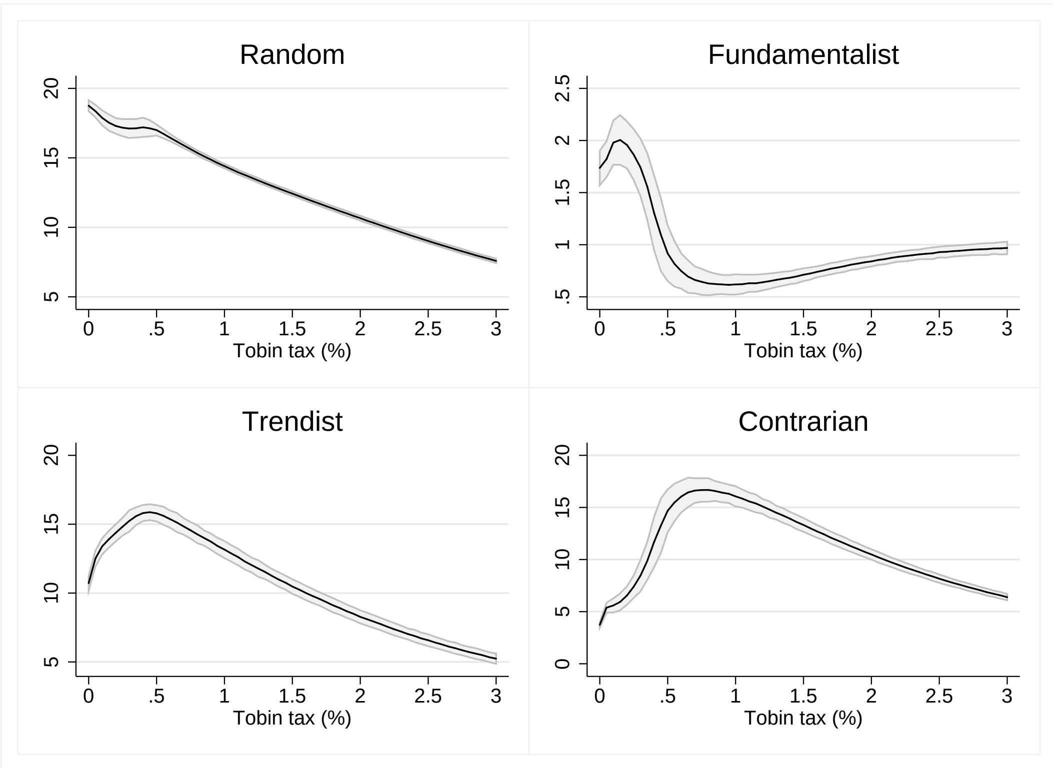
Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

Figure 18: Market activity by traders for $N = 10,000$

(a) Sold assets



(b) Purchased assets



Note: The bands represent a 95% confidence level from the Monte Carlo simulation.

References

Aliber, R. Z., Chowdhry, B., & Yan, S. (2003). Some evidence that a tobin tax on foreign exchange transactions may increase volatility. *Review of Finance*, *7*(3), 481–510.

Andersen, T., Benzoni, L., & Lund, J. (2002). An empirical investigation of continuous-time models for equity returns. *Journal of Finance*, *57*(3), 1239-1284.

Andersen, T., Bollerslev, T., & Diebold, F. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The Review of Economics and Statistics*, *89*(4), 701-720.

Barndorff-Nielsen, O., & Shephard, N. (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics*, *2*(1), 1–37.

Bianconi, G., Galla, T., Marsili, M., & Pin, P. (2009). Effects of Tobin taxes in minority game markets. *Journal of Economic Behavior & Organization*, *70*(1-2), 231-240.

Bouchaud, J., Kockelkoren, J., & Potters, M. (2006). Random walks, liquidity molasses and critical response in financial markets. *Quantitative Finance*, *6*(02), 115-123.

Broadie, M., & Jain, A. (2008). The effect of jumps and discrete sampling on volatility and variance swaps. *International Journal of Theoretical and Applied Finance*, *11*(8), 761-797.

Brooks, C., Černý, A., & Miffre, J. (2011). Optimal hedging with higher moments. *Journal of Futures Markets*.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703-738.

Eichengreen, B., Tobin, J., & Wyplosz, C. (1995). Two cases for sand in the wheels of international finance. *The Economic Journal*, *105*(428), 162-172.

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, *38*(1), 34-105.

Giot, P., Laurent, S., & Petitjean, M. (2010). Trading activity, realized volatility and jumps. *Journal of Empirical Finance*, *17*(1), 168-175.

Hamilton, J. (1994). *Time series analysis* (Vol. 10). Cambridge University Press.

Hanousek, J., Kočenda, E., & Novotný, J. (2012). The identification of price jumps.

Monte Carlo Methods and Applications, *18*(1), 53–77.

Hu, S. (1998). The effects of the stock transaction tax on the stock market-experiences from Asian markets. *Pacific-Basin Finance Journal*, *6*(3-4), 347-364.

Jacod, J., & Shiryaev, A. (1987). *Limit theorems for stochastic processes* (Vol. 288). Springer-Verlag Berlin.

Joulin, A., Lefevre, A., Grunberg, D., & Bouchaud, J.-P. (2008). Stock price jumps: News and volume play a minor role. *ArXiv e-prints.*

Keynes, J. M. (2006). *The general theory of employment, interest and money.* Atlantic Publishers & Distributors.

Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, *26*(6), 893-921. doi: 10.1002/jae.1149

Lavička, H. (2010). *Simulations of agents on social network.* LAP Lambert Acad. Publ.

Lavička, H., Lin, L., & Novotný, J. (2010). Employment, production and consumption model: Patterns of phase transitions. *Physica A: Statistical Mechanics and its Applications*, *389*(8), 1708 - 1720. doi: 10.1016/j.physa.2009.12.046

Lee, S., & Mykland, P. (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies*, *21*(6), 2535–2563.

Liu, S., & Zhu, Z. (2009). Transaction costs and price volatility: New evidence from the Tokyo Stock Exchange. *Journal of Financial Services Research*, *36*(1), 65-83.

Mannaro, K., Marchesi, M., & Setzu, A. (2008). Using an artificial financial market for assessing the impact of Tobin-like transaction taxes. *Journal of Economic Behavior & Organization*, *67*(2), 445-462.

Mathevet, L., & Steiner, J. (2012, April). *Sand in the wheels: A dynamic global-game approach* (Working Paper No. 459). CERGE-EI.

Merton, R. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*, *3*(1-2), 125-144.

Palley, T. (1999). Speculation and Tobin taxes: Why sand in the wheels can increase economic efficiency. *Journal of Economics*, *69*(2), 113-126.

Pan, J. (2002). The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics*, *63*(1), 3-50.

Raberto, M., Cincotti, S., Focardi, S. M., & Marchesi, M. (2003). Traders' long-run wealth in an artificial financial market. *Computational Economics*, *22*(2), 255–272.

Shiller, R. J. (2005). *Irrational exuberance.* Princeton University Press.

Tobin, J. (1978). A proposal for international monetary reform. *Eastern Economic Journal*, *4*(3-4), 153-159.

Umlauf, S. (1993). Transaction taxes and the behavior of the Swedish stock market. *Journal of Financial Economics*, *33*(2), 227-240.

Westerhoff, F. (2003). Heterogeneous traders and the Tobin tax. *Journal of Evolutionary Economics*, *13*(1), 53-70.

Westerhoff, F., & Dieci, R. (2006). The effectiveness of Keynes-Tobin transaction taxes when heterogeneous agents can trade in different markets: A behavioral finance approach. *Journal of Economic Dynamics and Control*, *30*(2), 293-322.

Working Paper Series
ISSN 1211-3298
Registration No. (Ministry of Culture): E 19443

Individual researchers, as well as the on-line and printed versions of the CERGE-EI Working Papers (including their dissemination) were supported from institutional support RVO 67985998 from Economics Institute of the ASCR, v. v. i.

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University in Prague, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute of the ASCR, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
Printed by CERGE-EI, Prague
Subscription: CERGE-EI homepage: http://www.cerge-ei.cz

Phone: + 420 224 005 153
Email: office@cerge-ei.cz
Web: http://www.cerge-ei.cz

Editor: Marek Kapička

The paper is available online at http://www.cerge-ei.cz/publications/working_papers/.

ISBN 978-80-7343-315-4 (Univerzita Karlova. Centrum pro ekonomický výzkum
a doktorské studium)
ISBN 978-80-7344-308-5 (Akademie věd České republiky. Národohospodářský ústav)

CERGE-EI
P.O.BOX 882
Politických vězňů 7
111 21 Praha 1
Czech Republic
http://www.cerge-ei.cz