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Non-Value-Added Tax to improve market fairness and quality

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Abstract

The promotion of both market fairness and efficiency has long been a goal of securities market regulators worldwide. Accelerated digital disruption and abusive trading behaviors, such as the GameStop mania, prompt regulatory changes. It is unclear how this "democratization" of trading power affects market fairness as economies cope with pandemic-driven shifts in basic systems. Excessive speculation and market manipulation undermine the quality of financial markets in the sense that they cause volatility and increase the pain of bubble and crash events. Thereby, they weaken public confidence in financial markets to fulfill their roles in proper capital allocation to irrigate the real economy and generate value for society. While previous studies have mostly focused on market efficiency, our study proposes a tool to improve market fairness, even under periods of stress. To encourage value generation and improve market quality, we advance a graduated Non-Value-Added Tax that we implement in an agent-based model that can realistically capture the properties of real-world financial markets. A profitable transaction is taxed at a higher rate if it does not enhance the efficiency measured by deviation from fundamentals. When an agent locks in profit not supported by fundamentals but driven by trend-following strategies, the generated profit is taxed at various rates under the Non-Value-Added Tax regime. Unlike existing financial transaction taxes, the non-value-added tax is levied on profit rather than on price or volume. We show that the proposed tax encourages profitable trades that add value to the market and discourages valueless profit-making. It significantly curtails volatility and prevents the occurrence of extreme market events, such as bubbles and crashes.

Keywords: Market fairness, Financial transaction tax, Non-Value-Added Tax, High-frequency trading, Bubbles and crashes, Efficiency

JEL Classification: G14, D84, D85, E47, I31

Introduction

Amid the exponential growth of high-frequency trading (HFT), dark pools and digital disruptions, such as the "Flash crash" and the "GameStop rally", regulatory authorities worldwide have a mandate to ensure that financial market practices are trustworthy and markets are fair and efficient. However, to date, the focus has been predominantly placed on market efficiency, while studies that address market fairness remain scarce, the latter being difficult to apprehend and measure. In fact, the investigation of *"high-frequency* *market microstructure"* elucidates two policy issues of particular interest: market linkages and market fairness (O'Hara 2015). When markets become faster, they do not necessarily become fairer.

Frankfurter (2006) presents the theory of fair markets (TFM) as an alternative to the efficient-market hypothesis (Fama 1970). The author argues that the statements *"let the market alone"* and *"market knows better" "are a myth created and nurtured by those who want to take advantage of their political power to keep any regulatory body off their hands"*. To promote market fairness, a regulatory framework should be established to guarantee fair and unimpeded competition, which can improve the allocation of resources and eliminate opportunistic trades. In light of the global meltdown in 2008, several studies, such as Mullineux (2010) and Marti and Scherer (2016), have discussed the need for financial market regulations to protect individuals and businesses against the *"monopoly powers of large suppliers"* and the complexity of some structured financial products. Since then, the connection between financial markets and social welfare has gained traction, as many researchers, such as Jonath and Goldwater (2018), have devoted close attention to studying new regulatory mechanisms to combat financial instability and prevent future financial crises and, more particularly, promote financial market transactions that add value to society. Marti and Scherer (2016) stress the importance of linkages between financial innovation, including new types of derivatives, new processes, new market organization, and new regulations, and social welfare.

In July 2015, Mary Jo White, who served as the 31st Chair of the SEC, called for market reforms to curb unfair advantages of HFT, including reining in HFT itself and monitoring dark pools and other prohibited trading practices in the world's largest stock market. However, she clearly states that *"the SEC should not roll back the technology clock or prohibit algorithmic trading (AT), but should assess the extent to which computer-driven trading may be working against investors rather than for them"*.

Both fairness and efficiency are crucial considerations in market design and regulation. However, as previously mentioned, the existing literature and regulators focus on market quality (efficiency, liquidity, and volatility), while they neither define nor measure market fairness. Boatright (2010) states that fairness is a notoriously complex moral concept that has a wide range of applications and standards. He observes that the word "fair" can mean a variety of things in different contexts. The U.S. Congress also employs the word "fair" frequently in the Dodd–Frank bill, yet it does not define it. It only came up with a narrow definition of the word "unfair" for consumer financial products instead[1]. Regarding financial markets, given their complex features and designs, as well as the explosive growth of AT, achieving fairness among market participants seems to be one of the most challenging tasks for regulatory authorities. Studies that address fairness in financial markets are scarce. Angel and McCabe (2013) consider different notions and dimensions

[1] Unfair is (A) the act or practice that causes or is likely to cause substantial injury to consumers which is not reasonably avoidable by consumers; and (B) such substantial injury is not outweighed by countervailing benefits to consumer."

of fairness in financial markets identified by Shefrin and Statman (1993)[2] and examine the fairness of HFT practices based on these definitions when it applies.

Aitken et al. (2018) also define and measure both market efficiency and market fairness in an evidence-based policy framework they build using a series of empirical proxies. Their model allows them to examine the exponential growth in AT on the London Stock Exchange and NYSE Euronext Paris for the period 2003 to 2011. They define market fairness as "a market in which prohibited trading behaviors are minimized". Irrefutably, some of the manipulative uses of HFT are unfair under any notion. In line with Angel and McCabe (2013) and Aitken et al. (2018), we define market fairness as the ability of a market structure and its regulatory framework to guarantee unimpeded competition, while curbing excessive speculation and market manipulation.

Herein, we contribute to discussions on non-trivial issues, such as market fairness and social welfare, in financial markets, where both concepts seem to be compromised. We develop a tool referred to as the Non-Value-AddedTtax (NVAT) inspired by the work of Jonath and Goldwater (2018)[3] to reduce the negative effects of HFT, including market instability or market manipulations, without losing the benefits it brings to the market (e.g., market efficiency or price discovery).

Thus, we start by defining the term "value" in our model. In fact, "value" in financial markets refers to trades that improve market quality; in other terms, trades that contribute to informational efficiency and price discovery, provide for market liquidity, and reduce market volatility. The NVAT we aim to develop to curb speculative activities is quite different from the financial transaction taxes (FTTs) widely discussed and implemented most notably in the European Union (EU). The main difference is that the NVAT is levied on profit, rather than on price, which assimilates it into an income tax rather than a sales tax. Defined as a tax on profit, it does not suffer from the main drawback of FTTs, which may result in paying taxes even when incurring losses. Additionally, the NVAT simplifies reporting and transparency requirements, reduces administration costs, and minimizes harmonization complexities.

Evidently, the NVAT addresses two major drawbacks forcing some governments to consider withdrawal from the FTT they have implemented[4]. First, the NVAT eliminates the concern about rate variations applied to different financial instruments, such as stocks vs. derivatives. With the NVAT's profit-based tax rate table, divided into tiers of value-added content in transactions, the identity of specific financial instruments is irrelevant. Second, it lessens the confusion and difficulty of harmonizing the tax base among transacting institutions in different territorial locations. As the tax is applied to profit, the NVAT only applies to profitable transactions (selling associated with initial

[2] The different fairness notions observed by Shefrin and Statman (1993) are freedom from coercion (participants are not free to participate or not in a transaction), freedom from misrepresentation (fraud is not involved), equal information (no insider trading), equal processing power (no disparity in the ability of participants to process information), freedom from impulse (participants are protected from their own irrational impulses, efficient prices (prices reflect all the information available in the market), equal bargaining power (no gross disparity in the power relationships between the participants)).

[3] Introducing the Non-Value-Added tTx (NVAT): A fiscal tool to combat financial instability. In *Fifth International Symposium in Computational Economics and Finance, Paris, France*. (http://www.researchgate.net/publication/350558216_Introducing_the_Non_Value_Added_Tax_NVAT_A_Fiscal_Tool_to_Combat_Financial_Instability).

[4] Tax Journal, "EU's financial transaction tax: where are we now?", 5 October 2018. https://www.taxjournal.com/articles/eu-s-financial-transaction-tax-where-are-we-now-05102018.

buying and buying associated with initial short selling). In both cases, all the data needed to manage the tax collection are already recorded because they consist of the price the seller pays and the price she receives. We can then compute the profit of each seller, measured by the change between these prices. Hence, the NVAT brackets are tied to a ratio of cost to profit, both of which are recorded for each transaction. Buyer location is inconsequential, and no new bureaucracy is required for data acquisition or transparency. Moreover, the NVAT makes the public partner in the upside rewards as well as in downside risks in the sense that in the last global crisis of 2008, the public has been called on to bail out too-big-to-fail institutions, which is unfair. The tax collection process under the NVAT we propose adds to market fairness because it can benefit national treasuries in support of public programs in good times.

As the NVAT applies to profitable trades, we clarify how our model handles a trade's profit. We compare the profit of a trade to the variation in the fundamental value between two trade points. If the price variation is higher than the variation in the fundamental values, the agent will realize an extra profit that is not supported by fundamental information. This extra profit can be explained by the momentum or trend component. The momentum-based extra profit is taxed based on NVAT rate regimes. We introduce an agent-based model that allows us to investigate the effect of the new regulatory tool's implementation on stock markets from both structural and behavioral perspectives. We contribute to the FTT debate by studying whether and how market volatility and trading activity are influenced by the suggested profit-based tax. We develop a simulator that acts as an artificial financial market wherein we compute a wide range of volatility and efficiency measures to grasp different dimensions of market quality. This computational–experimental approach based on simulations is widely employed in science, and more specifically, in addressing the introduction of financial regulations (see Literature review section). In our case, this experimental approach enables us to perform several validation tests and hypothesis testing to provide insights to regulators into fiscal regulatory policies. Noticeably, the tax we examine deals better with the objectives of stabilizing the market, discouraging speculation, and improving market fairness.

The remainder of the paper proceeds as follows: we first offer a literature review of existing FTTs, and we set representative models for implementing the NVAT as an FTT applied to traders' profits thereafter. Next, we discuss the results of the simulations in terms of tax-collecting capacity and the impact of the tax on market quality. We also examine its effect on market quality in extreme market events, such as flash crashes and bubbles. Finally, we draw conclusions on how the NVAT can be applied to influence trading behaviors, in favor of increased market fairness and a reduced income inequality gap that is growing increasingly worrisome.

Literature review

The existing literature focuses on FTTs that are applied on prices but not on profits. Their impacts on volatility and market liquidity show mixed results. With regard to volatility, Dooley (1996), Kupiec (1996), Subrahmanyam (1998), Amihud and Mendelson (2003), and many others identify a negative effect of FTT implementation on market liquidity, thus automatically amplifying market volatility by driving away rational agents. The latter is supported by Baltagi et al. (2006), Pomeranets and Weaver (2011), and

Huber et al. (2014), who correlate volatility with transaction taxes. However, few studies, such as Roll (1989), Saporta and Kan (1997), and Liu and Zhu (2009), relate an inverse or insignificant relationship between FTTs and volatility after investigating different markets and locations. Deng et al. (2014) conclude that the impact of an FTT on the market volatility will ultimately depend on the composition of a market's trader population. Moreover, interested in the behavior of noise traders and their impact on the market, Stiglitz (1989), Summers and Summers (1989), and Eichengreen et al. (1995) show that FTT dampens market volatility by discouraging noise traders. Song and Zhang (2005) and Bloomfield et al. (2009) confirm that an FTT drives away both rational and noise traders. Hence, its implementation reduces the market volume without affecting the spreads and prices, with at most a weak effect on the informational efficiency of prices.

Regarding the impact of FTTs on market liquidity and informational efficiency, the literature is relatively scarce. We refer to Frino and West (2003), Bloomfield and Wang (2006), Baltagi et al. (2006), Liu and Zhu (2009), and Pomeranets and Weaver (2011), who find a negative impact of FTT/transaction costs on the bid–ask spread, as a measure of market liquidity as well as on informational efficiency. Meyer et al. (2013) and Colliard and Hoffman (2017) consider that an FTT is sensitive to the composition of the trading floor population, the characteristics of the asset treated, and the market microstructure. Thus, they suggest that policymakers must be aware of the linkages between tax design and investor behavior before introducing an FTT. Veryzhenko et al. (2017) implement a tax on canceled orders by high-frequency traders (HFTs), using an agent-based financial model. The authors show that HFT liquidity is short-lived and that the implementation of a tax reduces HFT activities, which seems to have an insignificant impact on market volatility and market liquidity as measured by bid/ask spreads, while only dollar volumes decrease. The authors also show that reducing HFT activities leads to less efficient markets as the deviation from the fundamentals increases.

Additionally, Morone et al. (2020) discuss the effects of FTT on information mirages. The authors thoroughly investigate the impact of FTT implementation on a financial market where noise traders are unaware of whether privileged information fluctuates in the market. They show that the introduction of a tax does not affect the occurrence of an information mirage, improve market efficiency, and reduce the number of transactions.

Most of these FTTs discussed in the aforementioned studies are variations of currency taxes, such as Spahn (1995) and Tobin (1978), designed in the past several decades to keep the excesses in the currency market in check. While a Tobin transaction tax may reduce market liquidity, it also limits the desired stabilizing effect of such a tax. Demary (2011) confirms the observations of Westerhoff and Dieci (2006) that under a tax rate of 0.1%, approximately 80% of foreign exchange traders forgo trading, thus decreasing liquidity on the foreign exchange market. Finally, in 2015, the Tax Policy Center of the Urban Institute and the Brookings Institution published a summary of the general theory behind the FTT and described its status among the G-20 and major economies worldwide as well as its revenue potential in the U.S. (Burman et al. 2015). The report also offered a comparative study of the implementation methods in use and of those that were still under discussion. It elucidates the main weaknesses of the FTT approaches due to their rates and their application to gross rather than net revenue. The author concludes that the FTT, at the rates being proposed, would discourage all trading, not only speculation and rent-seeking, increase market volatility rather than curb it, and possibly create new distortions among asset classes and across industries, thus hurting market fairness and social welfare. Finally, according to Burman et al. (2015), the FTT appears to be poorly targeted at the financial sector excesses that have led to the Great Recession. Nevertheless, it has been suggested to replace it with a financial activities tax (FAT) or value-added tax (VAT), assuming that these taxes might be more effective and less distortionary[5], especially if the goal of the tax is solely to have the financial sector pay and compensate the rest of the economy for the costs that have ensued from the financial crisis.

Both the FAT, defined as a profit-associated tax on the sum of bankers' excessive remuneration and bank profits, and the VAT, defined as a price-associated tax applied to the sum of profit and costs, provide no distinction between profits on transactions that generate value and those that do not. In addition, in taxing both profit (capital income) and costs (labor value) without differentiation, VAT adds a financial incentive to cut costs. In this way, the VAT, described as a regressive sales tax, encourages forces that clearly act to increase the capital-to-labor wealth gap. The NVAT, a more practical FTT, can optimistically mitigate market instabilities, such as those caused by the rapid expansion of non-value-added profit bubbles.

In light of the above-mentioned limitations of existing tax regimes and their ineffectiveness as FTTs in improving market quality, the NVAT appears to be superior with regard to targeting a fairer and enhanced financial market quality as well as encouraging profitable financial transactions that add value to society. To the extent that profit is simply defined as the amount of price remaining after the deduction of total costs to market, we interpret an NVAT levied on a profit as universally applicable, irrespective of whether or not that profit is considered profit, rent, or interest. In NVAT applications, profit, rent, and interest are elements of the same set—surplus. As elements, these set members have different characteristics, some of which may be shared with other members of the set. For example, we note that the set "fruit" contains certain elements, including apple, cherry, and alpine honeysuckle. The latter resembles cherries, yet is inedible and has a very low sugar content compared to the other two. In economics, the addition of modifiers, such as pure, economic, and normal, changes profit's characteristics, introducing sub-elements, such as normal and economic, within the profit element. Similarly, modifying interest with fixed, variable, compound, annual, and so on identifies sub-elements to that element. Rent's sub-elements, defined by gross, contract, economic, scarcity, and quasi, for example, all connect to each other with Ricardo's definition[6] tying them to the agrarian economy and in turn to its modifications as industrialization[7] and information[8]

[5] For discussion of FAT and VAT as financial transaction taxes: "A Fair And Substantial Contribution By The Financial Sector Interim Report For The G-20", International Monetary Fund, p. 18, April 16, 2010. (http://news.bbc.co.uk/2/shared/bsp/hi/pdfs/2010_04_20_imf_g20_interim_report.pdf)—republished online by Global Print Monitor on April 22, 2010. Retrieved 2018-01-19.

[6] "Rent is that portion of the produce of earth which is paid to landlord for the use of original and indestructible powers of the soil." David Ricardo, On the principles of political economy and taxation, 3rd ed., John Murray, London, 1821.

[7] "Rent is the income derived from the ownership of land and other free gifts of Nature." "Quasi Rent" arises on the manmade equipment and machines in the short period and tend to disappear in the long run." – Alfred Marshall, "On Rent", *Economic Journal*, Vol. 3, 1893.

[8] As Landlord morphed into Intellectual Property Owner, rents and therefore rent-seeking assumed increasing roles in fulfilling business profit motives. See Lachlan Carey, Amin Nasir "Something for Nothing? How Growing Rent-seeking is at the Heart of America's Economic Troubles", Journal of Public and International Affairs, May 01, 2018.

ages unfolded. Regardless of "flavor", rent's sub-elements share the taste of profit made without costs. In the case of rent-seeking, Gordan Tullock[9] compared rents collected by an intellectual property holder from activities that benefit both the holder and society with those derived from rents that profit the holder but harm a group or society as a whole. He labeled only the search for the latter as "rent-seeking". With this distinction, he indicates a clear division between profits that are productive and unproductive to society. He supports this contention with reference to his own earlier work[10], to that of Anne Kruger[11] and to the labeling of such rent seeking by Jagdish Bhagwati[12] as Directly Unproductive Profit-Seeking (DUP).

The idea behind non-value-added (NVA) profit matches that of DUP. However, there are two distinct differences between the two terms. First, for operational convenience, with value defined as cost to market in the financial market application of the NVAT addressed in our paper, one can precisely determine the value-added portion of each transaction. This is simply the price paid for the stock. This is important when designing a tiered NVAT table with tax rates increasing as the added-value fraction of proceeds decreases. Tax tier levels can be chosen to align with the hierarchy that policymakers wish to assign among the profit, interest, and rent sub-elements. Using this table to implement an NVAT, more evidently than DUP, describes the tax's purpose to drive social benefit while providing profiteers self-evident indication for lessening the tax impact by increasing added value. Second, there is inherent familiarity and desirability associated with the term "value-added", which are attached to its inverse "non-value-added", thus helping the public to understand and accept the aims of a tax on NVA profit.

Our study investigates the effect of NVAT implementation, which is also meant to limit and help to meet the costs of future crises, similar to some traditional FTTs, as called for by the G-20 ministers in April 2010[13]. We use an agent-based model, which is widely employed in scientific research and more recently by policy makers. Maymin (2009) uses an agent-based model to implement a deterministic trading strategy that generates complex and realistic returns with the first four moments identical to the empirical values of European stock indices. This allows the author to simulate the effects of a financial regulation that can either prick bubbles, prop up crashes, or both. In addition, Gerding (2007), Kikuchi et al. (2019), and Kikuchi et al. (2020) employ simulation-based models to analyze the effects of financial regulation on investor behavior (behavioral finance), financial stability, and financial institution behavior, respectively. More recently, real markets and HFTs routinely use artificial intelligence to simulate their trading model results[14]. Policy makers at the OECD also depend on their tax-benefit simulation model, TaxBEN[15], to explore the detailed mechanics of tax-benefit policies and reforms.

[9] Gordon Tullock, "Rent Seeking", *The Locke Institute*, 22, 1993.

[10] Gordon Tullock, "The Cost of Transfers", *Kyklos*, 24, 629-43, 1971.

[11] Anne Krueger, "The Potential Economy of the Rent-Seeking Society", *American Economic Review*, 64, 291-303, 1974.

[12] Jagdish Bhagwati, "Lobbying and Welfare", *Journal of Public Economics*, 14, 366-63, 1980.

[13] Ibid. pp. 8,9

[14] https://www.forbes.com/sites/forbesdallascouncil/2019/04/15/artificial-intelligence-in-stock-market-investing-is-it-for-you/?sh=7531cff65240.

[15] TaxBEN: The OECD tax-benefit simulation model Methodology, user guide and policy applications Dec 2020.

Experimental design

We run a series of experiments to capture the effect of the NVAT on traders' profits and market quality. First, we consider a set of simulations wherein we ignore taxes. This set serves as a benchmark. Thereafter, we incorporate taxes and run the simulations under the same initial settings and compare the results and observations with the benchmark, that is, the initial untaxed market, to examine the effect of profit-based tax on market quality.

We develop a simple synthetic model of the market, with only one risky security and N competing traders subject to the same institutional market design. Trading agents belong to a heterogeneous population and participate in a protocol organized in trading sessions or rounds. In each session, traders exchange only one unit of equity.

Market mechanism

In this study, we use the ArTificial Open Market (ATOM) platform[16] introduced by Brandouy et al. (2013). Developed as a large-scale experimental platform, ATOM offers three main interacting modules: (i) the market microstructure, whereby we define the mechanism of order routing and price fixing; (ii) the economic environment that generates exogenous information on corporate developments, dividend payout policy, and coupon changes; and (iii) an agent component that offers multiple types of agents with different utility functions, views, and strategies. Traders react to exogenous information (e.g., expected returns, estimated risks, etc.) and endogenous information (such as post-transaction information generated by agents' interactions), imposed restrictions, and market mechanism rules. Figure 1 depicts these components of the system and the interactions between them as multiple independent traders meet in the marketplace. The pseudocode, Algorithm 1, describes the agents' decision-making process.

Central order book

A market mechanism comprises a set of rules that define how we transform agents' orders into a series of transactions with their timing, price, and volume. In most simulation-based studies (Lux and Marchesi 2000; Pouget 2007; Pellizzari and Westerhoff 2009), the clearing price is computed based on aggregate excess demand and supply. In our study, we reproduce a realistic central order book market mechanism. The *central order book* we develop represents a continuous trading mechanism when multiple transactions are possible at each time step. All orders, called *limit orders*, are stored for execution according to a strict price–time priority on the two sides of the order book, that is, the bid (demand) and ask (offer). The highest demand price represents the best bid, while the lowest offer price represents the best ask. When a new buy or sell order arrives at the market, the execution conditions are checked. The market price is updated continuously, and all previous and current orders, timing, volume, and price of transactions are always visible to the public.

[16] http://atom.univ-lille1.fr.

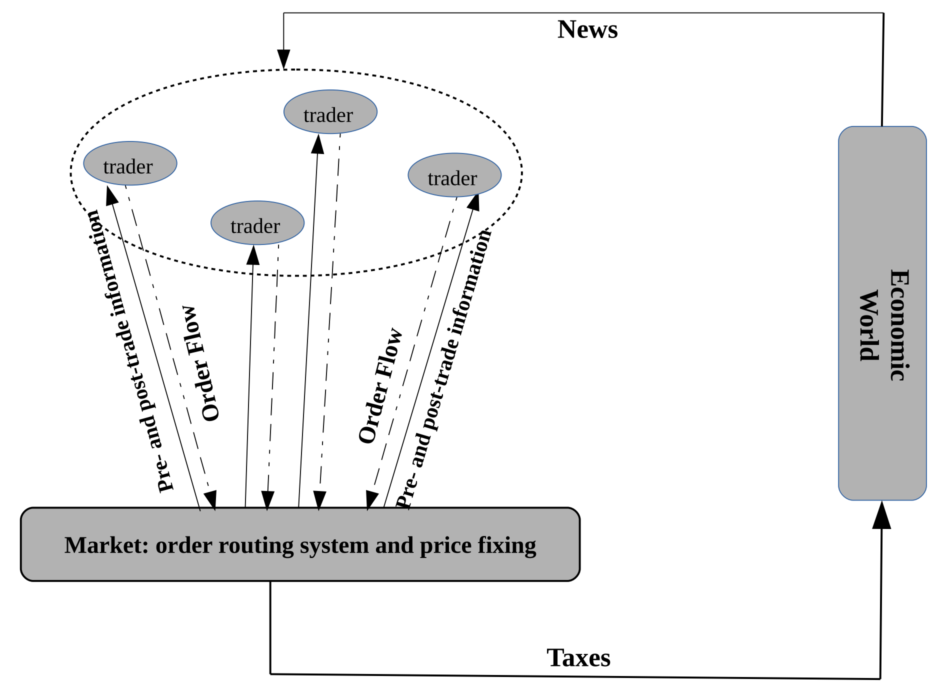


Fig. 1 Market organization and interactions

Time scale

A key element in all multi-agent systems is the scheduler that models the time scale. It manages the moment when agents act, orders are executed, and the price is fixed. A scheduler can be treated as a set of loops (or rounds) in the simulations; in each of them, agents can express their decisions to buy, sell, or do nothing. ATOM is also able to start each round by activating the same category of traders. In this way, we can simulate the privileged access of HFTs to the order book.

Moreover, the number of rounds determines the time granularity of the simulations. We consider 1000 time steps, which approximately correspond to a half-minute time scale or 8.5 hours of trading session. Because the choice of the trading frequency made by agents is essential for them to reach their investment objectives, we allow them in ATOM to decline the suggested trade decision generated by the simulator. In this manner, they can choose and set their trading frequencies. In our simulations, the trading frequency of fundamentalists (described below) varies from once per minute to once per hour, while the trading frequency for trend followers is set at a half-minute, as this type of agents can trade at the finest time grain.

Traders behavior

The main role of agents in the stock market is to analyze the information they obtain and make decisions in line with their selected strategies to translate their knowledge into buying and selling actions. Agents gather information and react relatively sensibly to it. The price dynamic is then a result of non-trivial interactions between traders, market microstructure, and regulatory rules. Furthermore, the price dynamic itself becomes a source of information (momentum signal) for investors, who trade accordingly and end up affecting market dynamics. Consequently, this creates a feedback loop.

Additionally, another type of information can potentially guide traders' decision-making; it is the firm-specific or fundamental signal. It is evident that there is no one agreed-upon formula to determine the intrinsic value of a stock. However, it can still be assessed based on the following factors:

- a top-down approach (including macroeconomic environment, the story of the stock, the trends of the pattern of operations, the organic growth versus strategic acquisition, etc.)
- bottom-up approach (among the important figures, we find the market-to-book ratio, the EPS, the P/E ratio, net present value, etc.; yet, it would be very simplistic to proceed to a comparison to P/E ratio in our analysis).

It also depends on the NVAT enforcer to delineate and define its proprietary measure of the fundamental or intrinsic value of the underlying instruments. In our study, for the sake of simplicity, we model the fundamental value dynamic of a stock by assuming that it follows a jump process in line with Foucault (1999); Pellizzari and Westerhoff (2009): $F_{t+1} = F_t + \sigma_t$, where $\delta_t \sim N(0, \sigma^\delta)$, for $t = \overrightarrow{1, N}$, where $F_t > 0$ and the initial fundamental value is $F_0 = 200$ (this value is randomly chosen as a starting point, and it does not significantly impact the results of simulations).

The fundamental value is organized in a matrix 1000×1000 (for 1000 rounds and 1000 repetitions) in all scenarios. Traders can trade based on this information or completely ignore it, depending on their heterogeneous preferences.

Fundamentalists are motivated by the real (fundamental) asset value. The fundamental value of a stock follows a jump process $F_{t+1} = F_t + \delta_t$, where $\delta_t \sim N(0, \sigma^\delta)$ is a normal random variable with a zero mean and constant standard deviation. A $\delta_t > 0$ signals a positive prospect; thus, investors expect a price increase. A $\delta_t < 0$ signals a negative prospect and a price decrease. The case of $\delta_t = 0$ denotes an ambiguous message that investors ignore when they form their own expectations.

Because we assume that agents are boundedly rational (or noisily informed), the fundamental value appears to be biased by ϵ_i, which determines the accuracy with which agent i interprets the fundamental information $E_{i,t}(P_{t+1}) = F_{t+1} + \epsilon_i$, $\epsilon_i \sim N(0, \sigma^\epsilon)$. Agents belong to a heterogeneous population with respect to their parameter ϵ_i, which is normally distributed with a zero mean and constant standard deviation σ^ϵ.

To decide whether to be short or long on a stock, an agent compares the current stock price P_t with his expectations $E(P_{i,t+1})$. If $P_t > E_{i,t}(P_{t+1})$, the stock is overvalued; hence, the agent can benefit from this deviation from fundamentals by placing a sell (ask) order. If $P_t < E_{i,t}(P_{t+1})$, the stock is undervalued; hence, the agent takes advantage of it by placing a buy (bid) order.

HFTs or high-speed trend followers do not consider the fundamental value, they try instead to detect trends and trade accordingly. They rely on historical price dynamics to anticipate future price variations.

$$|\frac{P_t - P_{t-n}}{P_{t-n}}| > \gamma_i. \tag{1}$$

The agents are heterogeneous with respect to the parameter γ_i of the minimal price variation and its interpretation.[17] In our model, trend followers buy (sell) when the stock value has been increasing (decreasing) over the last 10 to 100 rounds, which is reflected in the way we set parameter n. Their behavior can be described as positive feedback trading, as they detect a trend and reinforce it. Trend followers constantly seek trading opportunities and define their expectations as follows:

$$E_{i,t}(P_{t+1}) = P_t + \gamma_i(P_t - P_{t-1}) \tag{2}$$

where $E_{i,t}(P_{t+1})$ represents the expectation of agent i at moment t about future price P_{t+1}. P_t is the market-clearing price at moment t. γ_i is the sensitivity of agent i to the market trend $P_t - P_{t-1}$. This parameter γ_i can also be interpreted as the importance given to the momentum signal. This parameter is central in our model, where it identifies speculation activity. It is uniformly driven from the interval $U[0\%; 1\%]$. Investors sell (buy) when the last past clearing price is higher (lower) than his focal price expectations, $P_t > E_{i,t}(P_{t+1})$ ($P_t < E_{i,t}(P_{t+1})$). To sum up, traders would be interested in buying undervalued stocks and selling overvalued stocks based on their beliefs. This model of trend following strategy as well as parameters' initialization are inspired by the work of Biondi and Righi (2016).

Similar to Jacobs et al. (2004) and Jacobs et al. (2010), the agents in our simulations apply adaptive order submission, while expecting to maximize their profit. However, traders face a trade-off between the potential profit and the tax rate, as a higher profit means graduating into an upper tax bracket. Hence, they do not adhere to their expectations. They check the current state of the order book to optimize their final trade. In a double auction market, a profit-oriented buyer would propose a price that does not fully reflect his reservation or expected price (the maximum price he would be willing to pay), betting on the existence of a seller who would accept to fill this relatively low bid order. Similarly, a seller would propose a price that is higher than his reservation or expected price, betting on the existence of a bidder that is ready to buy at this relatively high price. Agents set the direction and price of their orders based on the last market price and the current state of the order book.

Non-Value-Added Tax (NVAT)

Next, we incorporate the NVAT into our model, whereby all traders involved in transactions update their cash and stock positions with respect to transaction price and transaction tax (NVAT). For each agent, we compute the profitability of the trade: buy low and sell high (as margin and short selling are not allowed) $\triangle_P = V_k(P_k - P_l)$ (dollar volume variation), where V_k is the volume sold at moment k at price P_k and initially bought at price P_l at moment l. We compare the profit of the trade to the variation in the fundamental value between these two points of time

[17] As we reproduce central limit order book market mechanism, agents' heterogeneity is a key element to guarantee a continuous trading.

Table 1 Examples of NVAT tax rate, where %*F* is the variation in fundamentals between two trades, %*P* is the percentage price variation between two profitable trades

Ratios	VRR (Value Recovery Ratio)	Tax Tier 1	Tax Tier 2	Tax Tier 3	Tax Tier 4
Regime 1					
VRR	%*F* /%*P*	0 to 0.10	0.11 to 0.66	0.67 to 1.00	1.01 to 19.0+
NVAT rate		75%	25%	15%	0%
Regime 2					
VRR	%*F* /%*P*	0 to 0.05	0.06 to 0.25	0.26 to 2.00	2.01 to 19.0+
NVAT rate		90%	75%	25%	5%
Regime 3					
VRR	%*F* /%*P*	0 to 0.05	0.06 to 0.25	0.26 to 2.00	2.01 to 19.0+
NVAT rate		50%	40%	20%	10%

The NVAT is applied only to the total profit that is not supported by fundamental information. We compute the profitability of the trade: buy low and sell high (as margin and short selling is not allowed) $\triangle_P = V_k(P_k - P_l)$ (dollar volume variation) where V_k is the volume sold at the moment *k* at price P_k and initially bought at price P_l at the moment *l*, then we compare this profit to the variation in the fundamental value between these two points of time $\triangle_F = V_k(F_k - F_l)$. If $\triangle_P > \triangle_F$ it means that an agent was able to realize an extra profit not supported by fundamental information

Table 2 Parameters and their initial values used in simulations

Parameter	Value	Description
N^{FD}	1000	Number of fundamentalists
N^{HFT}	200	Number of HFTs
$C_{i,0}$	20,000	Initial cash attributed at moment 0 to agent *i*
$S_{i,0}$	100	Number of stocks attributed at moment 0 to agent *i*
N_{rounds}	1000	Number of rounds per day
F_0	200.00	Initial fundamental value
ϵ_i	[-1;1]	Accuracy of fundamental value prediction by the agent *i*
γ_i	[0, 0.001]	HF traders' activation threshold

Each of our experiments consists of 1000 runs, each starting with the same initial conditions (initial wealth, stocks held, agent population) except the fundamental value. We average all the statistics of 1000 repetitions

$\triangle_F = V_k(F_k - F_l)$. If $\triangle_P > \triangle_F$, it means that the agent is able to realize an extra profit that is not supported by fundamental information. The latter can be explained by the momentum or trend component of the transaction. For instance, an upward trend is possibly initiated by the positive information specific to the concerned company (microeconomic level information), which can be exploited (confirmed and reinforced) by the trend followers (technical analysts). We can then tax the momentum-based extra profit according to the NVAT tax regimes. Three of these regimes are listed in Table 1. In our simulations, the NVAT is applied to the total profit, that is, NVAT payment $= V_k(P_k - P_l) \times NVAT_{rate}$.

Each of these experiments consists of 1000 runs, each starting with the same initial conditions (initial wealth, stocks held, agent population), except the fundamental value. Hence, we averaged all the statistics for 1000 repetitions. The parameters we use in our simulations are listed in Table 2. The parameter estimation is in line with empirical studies such as (Kirilenko et al. 2017; Colliard and Hoffman 2017; AMF 2017) and those using agent-based modeling research such as (Pellizzari and Westerhoff 2009; Veryzhenko et al. 2017; Oriol and Veryzhenko 2019).

It is worth mentioning that the NVAT is different from the corporate income tax. Here, we highlight four main differences:

- The NVAT forces attention on value-added content in financial transactions. Corporate income tax forces actions to reduce expenses.
- Traders can have control over lowering the NVAT rate by increasing the value-added content of transactions. This means that a profit made with little or no value-added benefit would be taxed at a higher rate than would the same profit made on transactions with higher value-added content. Corporate income tax makes no such distinction, especially one that raises awareness as the world addresses existential issues of climate change and sustainability.
- The NVAT can be collected immediately upon transaction because all the data needed for tax computation are recorded at the point of sale. In the case of NVAT replacement of the current FTT, this aligns NVAT collection implementation procedures with those of FTT. Corporate income tax payments follow the closing of periodic financial accounting records and audits, thus introducing delays and possible tax avoidance revisions into the tax collection process.
- Value content varies from one product to another. The NVAT tables can automatically assign tax payment amounts that will likewise change to accommodate this variation. Corporate income tax does not.

Furthermore, in the case of its use to replace current FTT inadequacies, it may not necessarily replace financial corporations' income tax.

Results and discussion

As we previously mentioned, we focus on three dimensions of market quality: market *volatility*, market *efficiency*, and market *liquidity*. For each experimental set, we generate 1000 series of runs per day. Based on these series, we compute multiple market quality metrics.

As a proxy for volatility, we use the average of the absolute and squared returns across each trading period:

$$|R_k| = \frac{\sum_{t=1}^{T} |R_{t,k}|}{T} \tag{3}$$

$$R_k^2 = \frac{\sum_{t=1}^{T} R_{t,k}^2}{T} \tag{4}$$

where t denotes each transaction, and T measures the total number of transactions within a given period k, $|R_{t,k}| = |ln(P_{t,k}) - ln(P_{t-1,k})|$ and $R_{t,k}^2 = \left(ln(P_{t,k}) - ln(P_{t-1,k})\right)^2$. Another volatility measure commonly used in the literature (LiCalzi and Pellizzari 2007) is the standard deviation of returns over a given period:

$$\sigma_k = \frac{\sum_{t}^{T} (R_t - \overline{R})^2}{T - 1} \tag{5}$$

Similar to LiCalzi and Pellizzari (2007), we assume that k represents the returns over the last 20 rounds. For the sake of comparability, all the data are aggregated (averaged) at a half-second grain, where 20 rounds represent a 10-minute time window. This determines the size of the moving window that we compute to create a series of statistics.

We measure *informational efficiency* using the absolute deviation between the price $P_{t,k}$ and the fundamental value $F_{t,k}$

$$\frac{1}{T}\sum_{t=1}^{T}\left|\frac{P_{t,k}-F_{t,k}}{F_{t,k}}\right| \tag{6}$$

Finally, market liquidity is computed as the total daily trading volume.

Difference-in-differences. To isolate the changes in metrics owing to policy implementation, we use the difference in difference *(DiD)* technique (Ashenfelter and Card 1985). The advantage of the DiD approach is that instead of comparing the averages of units, it compares the differences in the means of units of treated and control groups over time. We consider two groups and a 2-period case. Only one population is subject to the NVAT:

$$Y_i = \beta_0 + \beta_1 \cdot D^{treated} + \beta_2 \cdot D^{tax} + \tau \cdot \overbrace{D^{treated} \cdot D^{tax}}^{treated \times tax} + \varepsilon_i$$

We regress the metrics of efficiency, volatility, and liquidity Y_i on a set of treatment indicators, which include a dummy variable identifying the treated group $D^{treated} \in \{0,1\}$, a dummy indicating an after-tax period $D^{tax} \in \{0,1\}$, and the interaction of these two dummies $treated \times tax$, where τ is the parameter of interest. If the tax has a significant effect on the dependent variable, the regression returns a significant coefficient of the $treated \times tax$.

Based on Fig. 2a–d reported in the "Appendix", we identify a positive effect of the NVAT on controlling volatility (in all the three tax regimes). In fact, the results of the DiD test reported in Table 3 show that the absolute and squared returns decrease by 2.4% and 2%, respectively, with the implementation of the NVAT. The standard deviation also decreases by 1% on average. However, it negatively influences market liquidity and reduces trading volumes. Hence, based on all quantitative metrics, we conclude that market volatility decreases significantly with the introduction of an additional tax. This can be explained by the reduced trading activity. Moreover, the NVAT has a direct effect on speculators, dissuading them from entering unproductive trade. We also identify a reduction in the volume of orders and trading frequency. According to the DiD results, the trading volume decreases, on average, by 2.3%. However, the decreased trading volume should not be perceived as a simple dry-up of liquidity. The countervailing side is that a reduction in the volume of exchange means less frequent order submissions, updates, and cancellation of orders that may lead to dangerous market fluctuations. The graduated NVAT rate tables provide tools for marketplace supervision to manage balancing tradeoffs between liquidity and frenzy. In this manner, the NVAT removes some part of the speculative non-productive

Table 3 The impact of the introduction of different tax regimes on stock market efficiency, volatility and liquidity

Regime 1				**Regime 2**				**Regime 3**			
Abs. return				Abs. return				Abs. return			
Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value
4.991e−05	6.002e−06	0.0007072	$< 2e-16***$	− 9.077e−05	6.046e−06	0.002319	$< 2e-16***$	− 9.101e−05	6.095e−06	0.002315	$< 2e-16***$
Sqrt return				Sqrt return				Sqrt return			
Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value
− 3.369e−07	6.829e−08	0.0002423	$8.07e-07***$	− 5.997e−07	6.868e−08	0.0007787	$< 2e-16***$	− 5.988e−07	6.893e−08	0.0007779	$< 2e-16***$
σ_k				σ_k				σ_k			
Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value
− 4.829e−05	7.341e−06	0.0004386	$4.78e-11***$	− 8.083e−05	7.374e−06	0.001233	$< 2e-16***$	− 8.258e−05	7.442e−06	0.001275	$< 2e-16***$
Deviation from fundamental, %				Deviation from fundamental, %				Deviation from fundamental, %			
Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value
0.073625	0.013028	0.0003209	$1.6e-08***$	0.09409	0.01228	0.0005973	$1.83e-14***$	0.07187	0.01478	0.0002366	$1.16e-06***$
Volume				Volume				Volume			
Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value	Tax	(s.e.)	adj. R^2	*p* value
− 387.7	124.9	0.004303	$0.00193**$	− 695.3	120.2	0.01597	$8.46e-09***$	− 826.94	135.46	0.01782	$1.23e-09***$

Difference in differences analysis. (s.e.) = standard error of test. $R_t = log(P_t/P_{t-1})$ is the log return. *Sqrt.return* and *Abs.return* are respectively the squared and absolute returns. σ_k is the standard deviation computed based on 20 returns with a moving window of $k = 20$. The deviation from fundamentals represents the absolute difference between the fixed price and the fundamental value at the moment *t*. *Volume* represents the daily trading volume. Column *Tax* represents the effect of the NVAT on metrics of market quality. (s.e.), adj. R^2 and *p* value show respectively the standard error, the adjusted R^2 and the p-value of the test

Signif. codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ', 1

This table shows that the implementation of NVAT contributes to decreasing the absolute return, the squared return and the standard deviation but it negatively affects market liquidity since it reduces the trading volume. Yet, the decreased trading volume should not be perceived as a simple dry-up of liquidity. The countervailing side is that a reduction in volume of exchange means less frequent order submissions, updates, and cancellation of orders that may lead to significant market fluctuations. NVAT has a direct effect on speculators, dissuading them from entering into unproductive trades. The graduated NVAT tax rate tables provide the tools for marketplace supervision to manage balancing tradeoffs between liquidity and frenzy. In this manner, NVAT removes some part of speculative non-productive volume

volume. The reduced speculative activity leads to a calmer and less volatile market, as a direct effect of NVAT introduction. The statistics in Figs. 3 and 4 do not show a significant improvement in market efficiency. The quantitative results of the DiD test in Table 3 reveal that the introduction of the NVAT appears to have a negative effect on market efficiency, thereby increasing the deviation from the fundamentals. Furthermore, the NVAT not only impacts speculators but also dissuades some fundamentalists (who sell overvalued and buy undervalued stocks, based on their beliefs) from executing some usual trades. Consequently, the deviation from fundamentals increases, thus amplifying the NVAT collection.

Our results regarding the effect of NVAT on volatility are in line with those of Stiglitz (1989), Summers and Summers (1989), Eichengreen et al. (1995), Roll (1989), Saporta and Kan (1997), and Liu and Zhu (2009), who investigate the implementation of FTTs in different markets and locations and show that FTT dampens the market volatility by discouraging noise traders. Conversely, several studies (Dooley 1996; Kupiec 1996; Subrahmanyam 1998; Amihud and Mendelson 2003; Baltagi et al. 2006; Pomeranets and Weaver 2011; Huber et al. 2014, and many others) reveal that FTT implementation drives rational agents away, leading to an amplification in volatility. Most studies, such as Frino and West (2003), Bloomfield and Wang (2006), Baltagi et al. (2006), Liu and Zhu (2009), Pomeranets and Weaver (2011), Song and Zhang (2005), Bloomfield et al. (2009), and Veryzhenko et al. (2017), identify a negative FTT impact on market liquidity or volume, which is similar to the effect of introducing the NVAT on market liquidity.

Moreover, we show that implementing the NVAT does not improve market efficiency, which, however, contributes to amplify tax collection. Our findings are similar to those of Frino and West (2003), Bloomfield and Wang (2006), Baltagi et al. (2006), Liu and Zhu (2009), Pomeranets and Weaver (2011), Song and Zhang (2005), Bloomfield et al. (2009), and Veryzhenko et al. (2017), who confirm that an FTT has a weak or negative effect on the informational efficiency of prices as the deviation from fundamentals increases.

NVAT and Profitability of Trading. To understand the effect of the NVAT on the profitability of different strategies, we measure the end of period return, computed as $\frac{W_{i,T}-W_{i,0}}{W_{i,0}}$, where $W_{i,0}$ is the initial wealth of agent i, and $W_{i,T}$ is the end-of-day wealth of agent i. Figure 5 reports the distribution of end-of-period realized returns to fundamentalists and high-frequency traders. Figure 5a, b illustrate the effect of the NVAT on the profitability of trading. We do not find a significant difference in the means for both categories of traders. The average of the end-of-period return of HFTs in the taxed market is -0.46%, while in the untaxed market, it is -0.55%. The p-value of the t-test used to measure the equality of means of two series is 0.694. However, the results show that the NVAT can prevent traders from experiencing extreme losses.

How much tax revenues would the NVAT allow the government to collect? One intention of any tax is to raise substantial revenue. To estimate how much money the NVAT would collect, we measure the average daily tax payment made by different categories of traders. The findings are summarized in Fig. 6. Note that these figures are computed based on our artificial market model and can be scaled to markets of different sizes. On average, our representative group of high-frequency traders pays $45,000 with a standard deviation of $8,000, while the group of slow fundamentalists pays $380 with a standard deviation of $151. Fundamentalists and HFTs pay an average of $132,805 and $15,488,106, respectively, annually. Figure 6a, b illustrate the distribution of tax revenues collected from different categories of traders.

The results in the tables show that the NVAT significantly increases tax revenues without causing major distortions. Moreover, the NVAT clearly improves market volatility.

Extreme price movements

In the present section, we examine the effect of the NVAT on market quality in extreme market events, such as flash crashes and bubbles. In accordance with Bellia et al. (2018), we identify a mini-bubble (crash) as a strong and rapid price increase (drop), at least by 1.5% of the initial level, followed by a violent burst (recovery), within at most 12 minutes (24 rounds in our simulations). To be identified as a bubble (crash), the log price should retrace at least one-third of its initial rise (decline) within the above-mentioned time window. Such extreme price movements may ensue from practices that destroy liquidity. In this section, we consider two sources of potential bubbles and crashes: the first one is defined as an operational error and so called "fat finger", and it stems from the submission of a big volume order, which destroys liquidity. The second source of potential market instability is described as agents' synchronization or mimicking behavior, whereby crashes or bubbles emerge endogenously.

Exogenous liquidity shock

First, we create an extreme market event by introducing an aggressive market order, similar to that in Brewer et al. (2013). Such an order can be a market order with a volume larger than that available at the best price (Degryse et al. 2005). This order triggers a flow of transactions and causes the price to shift.

In our simulations, we specifically define the bubble as the result of placing a buy market order with a volume 20-times bigger than the average order size. According to Degryse et al. (2005), liquidity measures take approximately 20 best limit updates to return to their initial level. This explains the choice of the size or volume of the aggressive market order we need to place to create an extreme event. Such an order has an immediate effect on market dynamics. We then assess the reaction of the market before and after incorporating the NVAT, and we analyze its ability to reduce market volatility and hinder extreme market movements. We note that in a market not subject to regulations or taxes, the average price increase during a typical bubble is 4% with a standard deviation of 1.45%. However, in the taxed market under the NVAT regime, the mean price is 2.02%, with a standard deviation of 1%. Hence, we infer that HFT trend followers optimize their trading decisions and evaluate their potential final profit under different tax regimes based on their profit size. They consistently readjust the activation parameter Δ_i with respect to different tax rates. They tend to sell before they move up a tax bracket, even though the price is still increasing. Thus, they execute trades earlier in the direction opposite to the underlying trend and ease market correction. Figure plots the median cumulative return across 1000 simulations as a function of time in the harmonized time units, together with the 5% and 95% quartiles. The figure shows a steep upward trend, followed by a partial correction.

Consequently, traders face a trade-off between the profitability of trade and the tax rate. A higher trade profit is subject to a higher tax rate. Under the first tax regime we implement, the most frequent tax rate applied to profitable transactions is 25%, which seems to be a potential solution to the trade-off described above. We reveal a significant increase in the daily tax revenues from HFTs up to \$56,000 (compared with the initial \$45,000 under normal market conditions). The tax seems to dissuade HFTs from placing 20 million additional orders. Thereafter, we analyze the net positions of different categories of traders to understand their contribution to price correction. To measure the liquidity provision and liquidity consumption by different categories of traders, we use the monetary net trade imbalance. This is the difference between the funds invested in buying transactions and funds gained as a result of selling transactions. The negative net imbalance of a trading category during a bubble indicates that it contributes to price correction; however, a positive net imbalance during a bubble indicates that this category of market participants trade in the direction of the upward trend. We identify negative net positions for both categories of traders, HFTs, and non-HFTs in both scenarios. In the untaxed benchmark scenario, HFTs sell, on average, for \$5,108,292, while non-HFTs sell for \$3,235,573. In the taxed market under NVAT regimes, HFTs sell only for \$1,323,181, while non-HFTs sell for \$2,679,055. Hence, the price increase in the untaxed market is higher, thereby making selling transactions particularly profitable, and the volume of sales positions is even higher.

Endogenous liquidity dislocation

Next, we focus on the mimicking behavior of agents that can lead to self-reinforced bubbles and crashes (Kirman 1991; Lux 1995; Bookstaber 2017). Zha et al. (2020) propose a review of opinion dynamics' applications to financial markets where opinion evolution rules are used to model the microscopic dynamics among agents and study the trends, bubbles, and crashes from the macroscopic level. Similar to Brock and Hommes (1998); Lux and Marchesi (2000); Bookstaber (2017), we implement the contagion model driven by the mimicking behavior of traders with regard to expectations: traders can be influenced by trading decisions and performance of other market players; thus, they are capable of adopting a more profitable strategy to a certain extent. This switching is driven by the high profits of the mimicked strategies. Hence, the fractions of the resulting strategies vary immediately with the portfolio growth of agents adopting the successfully mimicked ones. We assume that agents have a short-term memory and only pay attention to the results of their neighbors in the last round.

Similar to Watts and Strogatz (1998), we assume a random network to describe the connections between agents. The linkage between agents is defined as a binary matrix $N \times N$

$$M_{i,j} = \begin{cases} 1, \text{if agents are connected }, \forall i,j = \overrightarrow{1,N} \\ 0, \text{otherwise} \end{cases} \tag{7}$$

As in Watts and Strogatz (1998), we assume that each agent is connected with $N/2$ neighbors (where $N = 1000$ is the number of agents in the simulations) and half of them initially follow the fundamentalist strategy, while the other half follow a trend-based strategy. We also assume that the graph structure is not rewired at each time step. Unlike

Watts and Strogatz (1998), we assume an asymmetric connection between agents, whereby if agent i can analyze the performance of agent j, it is unnecessary for agent j to observe the performance of agent i.

In line with Lux and Marchesi (2000), we compute the potential profit of fundamentalist i at moment t as the percentage change in price, which represents for fundamentalist i, the deviation of the last trade price from the expected fundamental value. As fundamentalists believe that the stock price will converge to its intrinsic or fundamental value, we have:

$$\pi_{i,t}^{FD} = \frac{F_t - p_{i,t}}{p_{i,t}} \tag{8}$$

where $\pi_{i,t}^{FD}$ represents the expected profit of the fundamentalist, F_t denotes the expected fundamental value, and $p_{i,t}$ is the price of the pending order at moment t submitted by agent i.

For a trend follower, the profit is computed as the percentage change in his pending order price (or his last trade price) $p_{i,t}$ from the last market price P_t:

$$\pi_{i,t}^{HFT} = \frac{P_t - p_{i,t}}{p_{i,t}} \tag{9}$$

Consequently, if agent i is initially a fundamentalist at moment t, he will compare the past average profit of the strategies followed by his neighbors. As in Brock and Hommes (1998); Westerhoff (2008); Pellizzari and Westerhoff (2009), if the average profit of HFTs is higher than that of fundamentalists $\pi_{t-1}^{HFT} > \pi_{t-1}^{FD}$, the agent will switch to the following trend with a probability of:

$$\Psi_t^{HFT} = \frac{e^{\pi_{t-1}^{HFT}}}{e^{\pi_{t-1}^{HFT}} + e^{\pi_{t-1}^{FD}}} \tag{10}$$

Accordingly, the probability to use fundamental analysis is $\Psi_t^{FD} = 1 - \Psi_t^{HFT}$.

Figure a shows the trajectory of the fraction of HFTs over 1000 time steps in the untaxed market. This trajectory illustrates the strong fluctuations and emergence of clusters of dominant strategies. A joint analysis of Fig. a, b reveals that with a given proportion of trend followers, the deviation from fundamentals is self-reinforced, which results in mini-crashes or mini-bubbles. These results are in line with the noise trader theory that stipulates that noise traders or trend followers would push rational investors sidelines and "create their own space" (Wen et al. 2019). Then, as the fundamentalist's potential profit is computed as the percentage change in price deviating from the fundamental value, generating bubbles increases the potential profit to the fundamentalist, who believes that the price will converge to its intrinsic value. The latter encourages the adoption of a fundamentalist strategy, which seems to be temporarily more profitable. Hence, the population of agents converge slowly to fundamental analysts. Consequently, the bubble bursts (or the crash is recovered) and the price gets corrected.

In fact, in our simulations, the population of agents never completely converges to one dominant strategy (total contagion of expectations). These results are consistent with those of Lux and Marchesi (2000) and the empirical analysis of Cont (2007). In the latter article, the author states that the investor's inertia explains the switching behavior, which leads to the emergence of clusters of strategies and the persistence of the magnitudes of price changes called volatility clustering. If the volatility is low, agents become more sensitive to news and generate high excess demand, thus increasing the amplitude of returns. If the volatility is high, agents become less reactive to news, which increases agent inertia and reduces the amplitude of returns.

That said, what would be the effect of the NVAT on the switching behavior (synchronization) and as a result, on the emergence of bubbles and crashes? Our simulations reveal that the NVAT is unable to completely eliminate speculative behavior or encourage all the market participants to adopt a long-term fundamental-based strategy. However, the NVAT significantly reduces the profitability of speculators and considerably reduces the size of speculators' emerging clusters. Consequently, the NVAT contributes to regulating the emergence of extreme price events, such as bubbles and crashes.

In the taxed market, HFTs' population becomes dominant (followed by at least 501 agents) 43.82 times on average, while in the untaxed market, HFTs dominate 59 times on average. If the tax is implemented, the number of HFT agents becomes 209 on average, compared to 304 agents in the untaxed market.

Furthermore, in the untaxed market, we determine an average of 34 episodes of extreme price variations of 1.5% (crashes or bubbles) over 12 minutes and 3 episodes with log-price variations higher than 3%. Upon the introduction of the NVAT, the number of episodes of 1.5% log-price variations is reduced by approximately a factor of 4. The statistics based on 1000 simulations show that the price declines or increases by more than 1.5% averages 9.27 times, with a standard deviation of 10.41 times in the taxed market. In the latter market, we identify only 1.34 episodes of extreme price movements of more than 3% on average.

Conclusion

This study brings attention to the fact that there are "value-added" and "non-value-added" activities, which have quite different effects on our financial system and the economy as a whole. We propose a new FTT to improve fairness in financial markets dominated by short-horizon, profit-oriented traders and to contribute to social welfare by discouraging excessive trading behaviors that do not add value to the market. We implement the NVAT in a simulation-based model. The NVAT is a graduated tax, whereby a transaction is taxed at a higher rate if it does not enhance market liquidity, preserve market stability, or strengthen market efficiency. We test the effect of the NVAT on order-driven continuous trading, where we show that it significantly reduces the profitability of traders relying heavily on momentum signals, considerably reduces volatility, but slightly decreases trading volume. Additionally, NVAT reduces the amplitude of extreme market movements resulting from exogenous liquidity shocks such as "fat finger" events. The NVAT reduces bubble formation dynamics and staves off dangerous financial fluctuations from "tipping points". As the NVAT is levied on profit and not on price, investors solve an equation of the profit/tax rate relationship and do not purely maximize their profit. This mechanism makes investors close their positions at the earlier stages of bubbles and contributes to price correction.

The NVAT encourages profitable trades that add value to the market and discourages valueless profit-making. Therefore, it will help to provide a common, robust self-regulatory framework that protects investors and improves market fairness. It works as an FTT but levied only on profits; thus, NVAT dissipates the rightful concerns held by traders who claim that current FTTs are costly to administer across borders and over a variety of trading products beyond shares. In fact, the application of NVAT only to profits suggests that a) buyers pay no transaction tax until they become sellers, so buyer location has no tax consequence, and b) replacing a tax on price with a tax on profit converts FTT from a sales tax to an income tax. With this in mind, *NVAT could significantly contribute to tax revenues without causing major distortions in market quality.* The data required for NVAT assessment are recorded at the moment of trade; no new bureaucracy is needed to gather additional or specific data. Policy adaptations may be enacted by adjusting the NVAT rate tables or regimes, which is common among regulators. Interestingly, the results of NVAT collections would give cluster analyzers another tool to recognize and detect fraud. The tiers of the NVAT table could set a predetermined cluster set within which sub-clusters relating to malfeasance may be discoverable. Because the volume of programmed trade is usually high, the population of sub-clusters will be sufficiently large for meaningful cluster analysis (Li et al. 2021).

Historically, the mitigation enacted to avoid total financial paralysis that endured during the worldwide 2008–9 crash showed that governments must step in as a last-resort guarantor against catastrophic, non-recoverable, financial institution losses. The truth behind their "Too Big to Fail" description forces the general tax-paying public to act as unwitting partners with financial institutions during their downside calamities. *In this respect, the NVAT ensures a fairer system, whereby it also makes financial institutions partners with the trading public in its upside profits. This power-sharing may exactly fit the need of the EU's vision, now amplified by pandemic realities, to achieve "a transparent market with clear rights and protections for EU citizens"*. The NVAT also contributes to more financial sustainability as it helps to dissuade financial institutions and individual investors from engaging in manipulative NVA trading practices that have given rise to financial crises in the past, such as regulatory arbitrage, flash trades, excessive leverage, and speculations. It generates large tax revenues that can benefit national treasuries in support of public programs in good times or contributes to covering the costs of financial crises when they occur.

Appendix

See Figs. 2, 3, 4, 5, 6, 7 and 8.

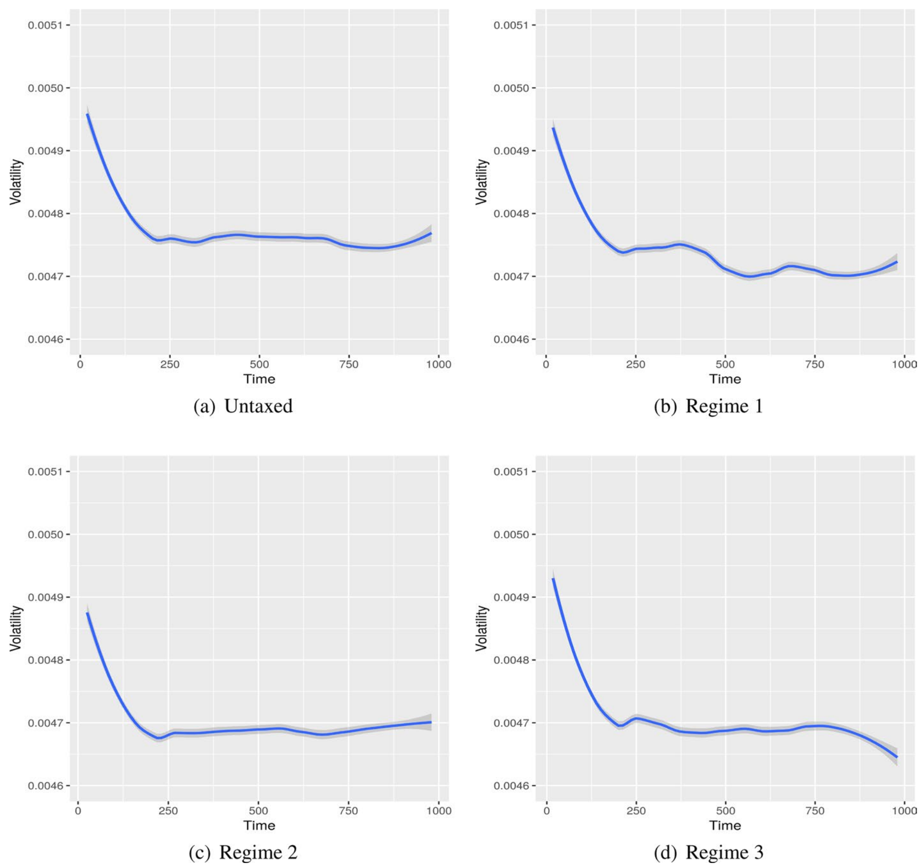


Fig. 2 Evolution of excess volatility. Excess volatility means that it excludes the volatility of fundamental value. Standard deviation is computed based on the moving window of 20 returns. The figures show that NVAT contributes to controlling market volatility (in all the 3 tax regimes)

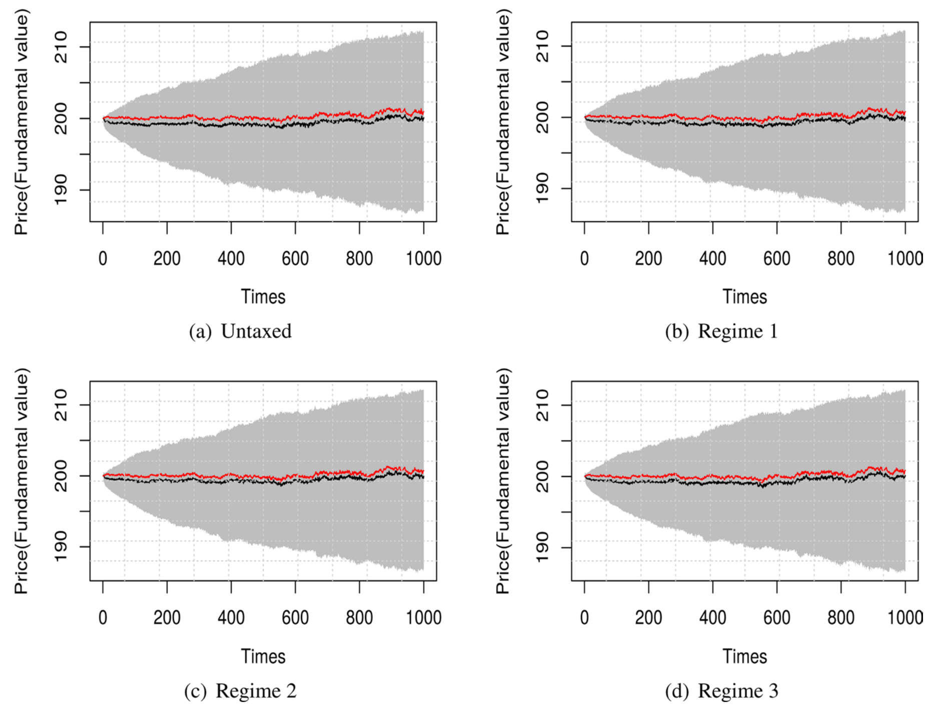
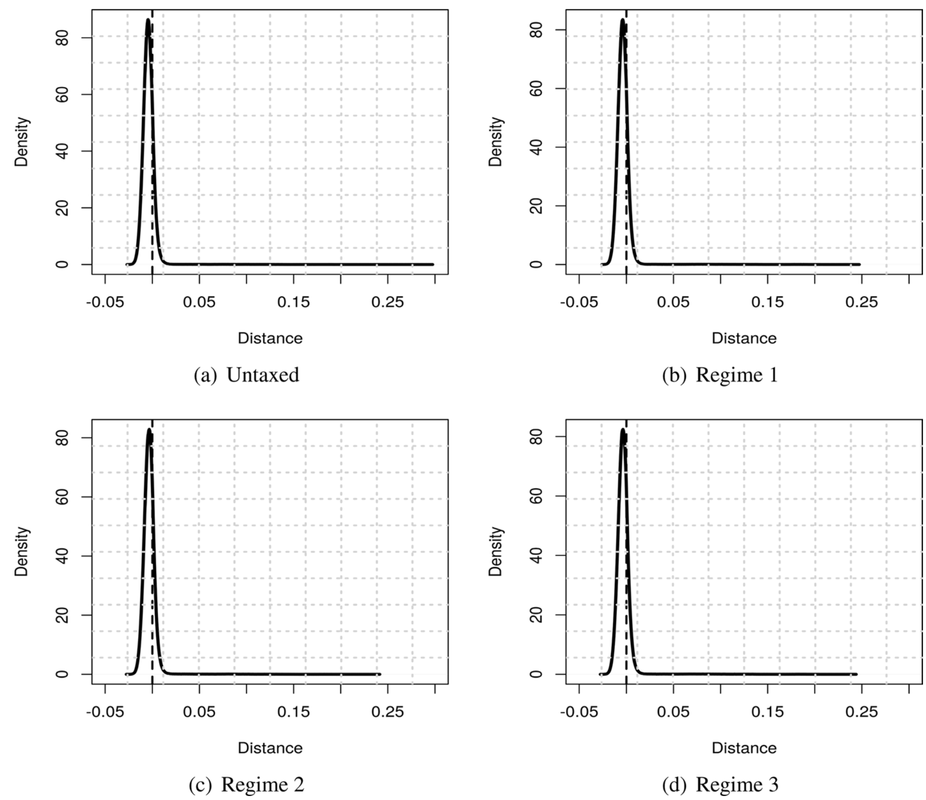


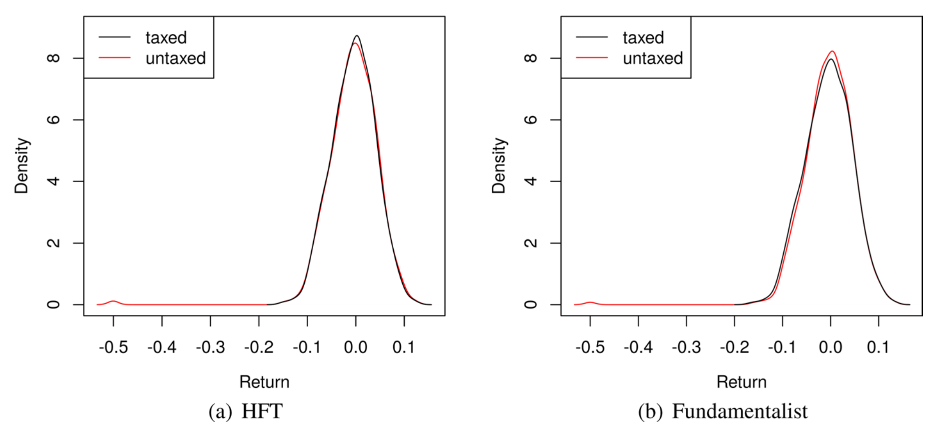
Fig. 3 Median price series (in black), median fundamental value series (red), grey area between 1st and 3rd quantiles. The figures do not show a significant improvement of market efficiency when implementing the NVAT, the deviation from fundamentals seems to increase. Yet, this amplifies the NVAT collection



(a) Untaxed (b) Regime 1

(c) Regime 2 (d) Regime 3

Fig. 4 Distribution of deviations from fundamentals. Similarly to Figures 3, the introduction of the NVAT seems to increase the deviation from fundamentals, which negatively affects the market efficiency. The bright side is that this magnifies the NVAT collection



(a) HFT (b) Fundamentalist

Fig. 5 Distribution of final profit—First tax regime. This figure reports the distribution of the end-of-period realized returns to Fundamentalists and High Frequency Traders. It illustrates the effect of NVAT on the profitability of trading, we show that there is no significant difference in profitability means for HFT and Fundamentalists . However, the implementation of NVAT makes it possible to prevent traders from incurring extreme losses

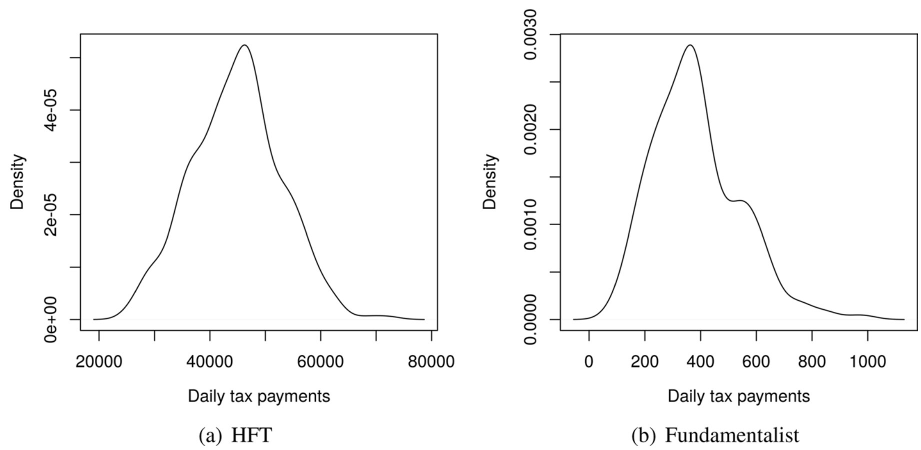


Fig. 6 Distribution of daily tax payment. In order to estimate how much money the NVAT would collect, we measure the average daily tax payment made by different categories of traders. The figures are generated based on our artificial market model and can be scaled to markets of different sizes. We show that our representative group of Fundamentalists and High Frequency Traders pay annually an average of $132,805 and $15,488,106, respectively. Hence, the NVAT significantly increases tax revenues, without causing major distortions

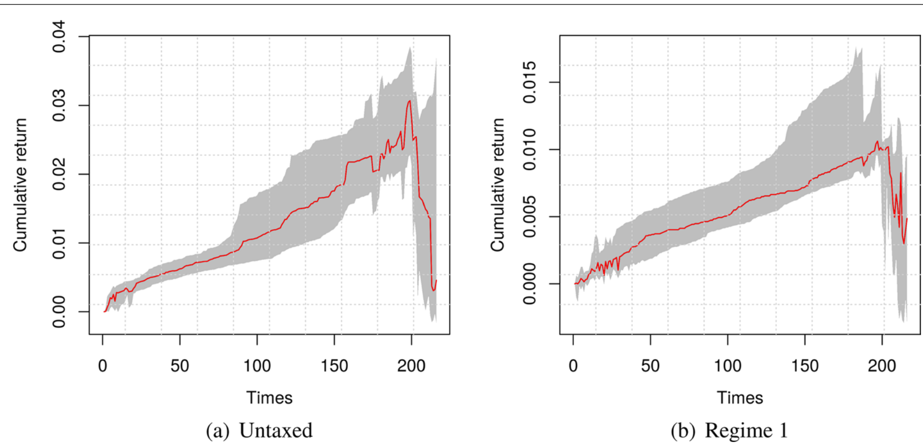


Fig. 7 These figures plot the median cumulative return (red curve) during a Bubble before and after NVAT implementation, across 1000 simulations, as a function of time in the harmonized time units, together with 5% and 95% quartiles (grey area). The figures show that NVAT significantly reduces the profitability of an extreme market event

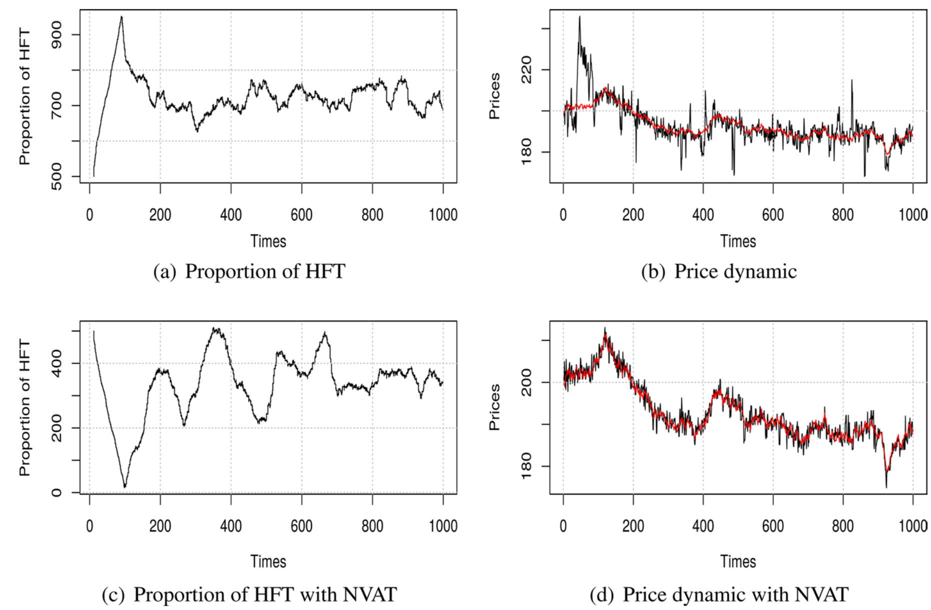


Fig. 8 Typical price dynamic and simultaneous evolution of proportion of HFT as the result of switching mechanism. As our simulator realizes continuous time asynhcronous (event-driven) trading, prices are aggregated at half-second time scale in order to improve their readibility and comparability. Each point reflects the last fixed market price at a given round. The first two figures correspond to untaxed market. The last two figures correspond to the market under Non-Value-Added Tax

Data: $E_{i,t}(P_{t+1})$, P_t, $\overline{P_D}$, $\underline{P_S}$
Result: Order
/* compare expectations with the current market price */
if $E_{i,t}(P_{t+1}) >= P_t$ **then**
  if $P_D \in \emptyset$ **then**
    /* bid side of the order book is empty */
    Direction = "Bid"
    Price $\sim U[P_t; E_{i,t}(P_{t+1})(1-NVAT)]$
    Quantity $\sim U[1; \frac{C_{i,t}}{Price}]$
  else if $E_{i,t}(P_{t+1}) >= \overline{P_D}$ **then**
    /* expected value is higher than the current best bid */
    Direction = "Bid"
    Price $\sim U[\overline{P_D}; E_{i,t}(P_{t+1})(1-NVAT)]$
    Quantity $\sim U[1; \frac{C_{i,t}}{Price}]$
  else
    /* expected value is lower than the current best bid */
    Direction = "Ask"
    Price $\sim U[E_{i,t}(P_{t+1})(1+NVAT); \overline{P_D}]$
    Quantity $\sim U[1; S_{i,t}]$
  end
else
  if $P_S \in \emptyset$ **then**
    /* ask side of the order book is empty */
    Direction = "Ask"
    Price $\sim U[E_{i,t}(P_{t+1})(1+NVAT); P_t]$
    Quantity $\sim U[1; S_{i,t}]$
  else if $E_{i,t}(P_{t+1}) <= \underline{P_S}$ **then**
    /* expected value is lower than the current best ask */
    Direction = "Ask"
    Price $\sim U[E_{i,t}(P_{t+1})(1+NVAT); \underline{P_S}]$
    Quantity $\sim U[1; S_{i,t}]$
  else
    /* expected value is higher than the current best bid */
    Direction = "Bid"
    Price $\sim U[\underline{P_S}; E_{i,t}(P_{t+1})(1-NVAT)]$
    Quantity $\sim U[1; \frac{C_{i,t}}{Price}]$
  end
end

return *(Direction, Price, Quantity)*

Algorithm 1: Decision making by agents. Traders differ with respect to the way they form their expectations about the future price dynamic $E_{i,t}(P_{t+1})$. Fundamentalists rely on received fundamental information F_{t+1} and proceed as follows: $E_{i,t}(P_{t+1}) = F_{t+1} + \epsilon_i$, where ϵ_i represents a bias in the interpretation of the fundamental value. It is determined as follows: $N(0, \sigma^{\epsilon})$. High-frequency trend followers extend past price trend $E_{i,t}(P_{t+1}) = P_t + \gamma_i(P_t - P_{t-1})$ where γ_i represents a sensitivity of agent i to the momentum signal. P_t market price at moment t, $\overline{P_D}$ is the best bid price, $\underline{P_S}$ is the best ask price, P_D is a set of bid orders (demand), P_S is a set of ask orders (supply), $S_{i,t}$ is the number of stocks held by the agent i at the moment t, $C_{i,t}$ is the available cash held by an agent i at the moment t, NVAT is the Non-Value-Added Tax, Ø denotes empty set, $U(x_1, x_2)$ is the uniform distribution in the interval $[x_1, x_2]$. Instead of maximizing their profit, traders face a trade-off between the potential profit and the tax rate, as a higher profit means graduating into an upper tax bracket. Hence, they don't adhere to their expectations, they set the direction and price of their orders based on the last market price and the current state of the order book.

Abbreviations
TFM: Theory of fair markets; HFT: High-frequency trading; HFTs: High-frequency traders; NVAT: Non-value-added tax; SEC: Securities and Exchange Commission; FTT: Financial transaction taxes; EU: European Union; FAT: Financial activities tax; VAT: Value added tax; ATOM: ArTificial Open Market; DiD: Difference in differences.

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Declarations

Competing interests
The authors declare that they have no competing interests.

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