How Noise Trading Affects Markets: An Experimental Analysis

By

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Abstract

We use a laboratory market to investigate the behavior of traders who lack informational advantages and have no exogenous reason to trade. We find that these uninformed traders behave largely as irrational contrarian “noise traders,” trading against recent price movements to their own detriment. The uninformed traders provide some benefits to the market: increasing market volume and depth, while reducing bid-ask spreads and the temporary price impact of trades. However, their noise trading also diminishes the ability of market prices to adjust to new information. A securities transaction tax reduces uninformed trader activity, but it reduces informed trader activity by approximately the same amount; as a result, the tax does not alter the impact of noise trading on the informational efficiency of the market.
How Noise Trading Affects Markets: An Experimental Analysis

I. Introduction

Noise traders play a ubiquitous role in the finance literature. Fischer Black [1986] dedicated his AFA presidential address to the beneficial effects of “noise” on markets, concluding that “noise trading is essential to the existence of liquid markets.” Shleifer and Summers [1990] and Shleifer and Vishny [1997] identified noise traders as the basis for the limits of arbitrage, arguing that noise trading introduces risks that inhibit arbitrageurs and prevent prices from converging to fundamental asset values. Noise traders in the guise of day traders have been disparaged for creating speculative pressures in asset prices both at home and abroad (Scheinkman and Xiong [2003]), while in the SOES bandits controversy the activity of day traders have been credited with enhancing price discovery (Battalio, Hatch, and Jennings [1997] and Harris and Schultz [1998]).

Despite this attention given to noise trading, there remains considerable debate regarding its precise role in financial markets, and over whether society is well advised to limit noise trading by taxation or other means, or to ignore it altogether due to its inconsequential nature in affecting market outcomes.

Partially explaining this confusion is that two strands of the literature emerged in the 1980s giving very different interpretations to the term “noise traders.” In the market microstructure literature, researchers use the terms “noise traders” and “liquidity traders” interchangeably to describe traders who do not possess fundamental information (e.g., Glosten and Milgrom [1985]; Kyle [1985]). While the motives of these traders are often left unspecified, the justification for their trading is generally assumed to be some

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1 See also “Day Trading Makes a Comeback” (Reuters, December 19, 2004), where day traders “were blamed for adding irrationality to an exuberant market”. Similarly, critics of globalization point to excessive short-term speculation in foreign currency trading as undermining the economic viability of developing countries, a motivation also cited for Thailand’s recent (short-lived) imposition of a Tobin Tax on foreign exchange (see “Central Bank measure reminiscent of Tobin Tax”, The Nation, December 21, 2006).
hedging or liquidity needs that induce changes in traders’ optimal portfolio holdings. Alternatively, the limits-to-arbitrage literature champions the existence of traders in the market who trade for reasons other than fundamental information, hedging, and liquidity shocks. As Shleifer and Summers [1990] note, this literature adopted the term “noise traders” to capture behavioral causes for trading not captured by these standard explanations, and in fact labeled itself the “noise trader approach to finance.”

In this research, we seek to clarify how noise trading affects markets. To do so, we conduct a series of experimental markets with three types of traders: traders who possess fundamental information (henceforth termed “informed traders”); traders who have to trade for exogenous reasons that stand for various consumption and risk sharing needs (“liquidity traders”); and “uninformed traders” who have no exogenous reasons to trade nor do they have valuable fundamental information. A particular advantage of experimental markets is that these uninformed traders are free to choose whatever strategies they prefer, providing a framework to investigate whether their trading behavior does, in fact, gives rise to “noise trading”.

We use our experimental data to shed light on the validity of three different ways in which these uninformed traders might behave. First, they might act as skillful technical traders who exploit information in the order book to earn a profit, as SOES bandits are presumed to do in the analysis of Harris and Schultz [1998], or similarly they could use information about price movements as uninformed traders do in the model of Hong and Stein [1999]. In either case, we would expect the uninformed traders to make positive profits, and to cause an increase in both market volumes and bid-ask spreads (because they are taking limit orders, rather than providing them). Second, the

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2 Glosten and Milgrom [1985; pg. 77], for example, note that such trading “may arise from predictable life cycle needs or from less predictable events such as job promotions or unemployment, deaths or disabilities, or myriad other causes.”

3 The limits-to-arbitrage literature features noise traders who trade on the basis of mistaken fundamental information as well as noise traders who trade based on rules in the spirit of technical analysis (e.g., looking at past prices of the security). We chose to focus the experiment on the latter type of noise traders, as it allows traders to pursue strategies without being influenced by exogenously given mis-information.
uninformed traders might rationally supply liquidity to the market, providing a service to liquidity traders by adding risk-bearing capacity (i.e., acting as market makers as in Grossman and Miller [1988]). With this behavior, we again expect to find positive profits, as well as greater depth in the book, smaller bid-ask spreads, and smaller temporary price impacts of trades. Finally, the uninformed traders might behave as irrational “noise” traders who act as if they have information when they do not, as in the classic description by Black [1986]. They could follow various technical trading rules or “popular models” as in Shiller [1984, 1990], employing positive-feedback trading strategies (e.g., De Long et al. [1990]) or possibly behaving as contrarians. Regardless of strategy, such noise traders would be expected to lose money on average, and could have varying effects on market liquidity and efficiency.

Our basic definition of noise traders can be traced back to Black [1986] and even earlier to the concept of noise in the rational expectations equilibrium models: these are traders who lose money on average and, hence, resolve the Grossman-Stiglitz conundrum of how informed trading is compensated in an informationally efficient market. As such, evidence that our uninformed traders behave like skillful technical traders or rational market makers would not put them under the category of noise traders. On the other hand, finding evidence of losses on technical trading strategies would demonstrate to us that such uninformed traders endogenously generate noise trading and would enable us to evaluate the impact of noise traders on the market.

We find that the uninformed traders in our experiment appear to act as irrational contrarian traders. Consistent with such behavior, adding these traders to the market dramatically increases trading volume, particularly when the fundamental value of the security (known collectively by the informed traders) is far from the prior expected value.

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4 There is an empirical evidence that individual investors in various countries trade in a contrarian fashion (e.g., Choe, Kho, and Stulz [1999], Grinblatt and Keloharju [2000, 2001], Richards [2005], Kaniel, Saar, Titman [2006]). For experimental evidence consistent with contrarian behavior see Bloomfield, Tayler, and Zhou (2007).
Skillful technical traders would be expected to earn higher profits when values are extreme by exploiting any sluggishness in price movements; however, the uninformed traders in our markets consistently lose money, and they lose the most when values are extreme because they act as (unwise) contrarians. Noise trading generated by the uninformed traders harms market efficiency because the uninformed traders’ contrarian strategies keeps prices from adjusting to new information when prices are far from true values. Interestingly, uninformed traders make transaction prices more efficient when security prices are not extreme, because the additional liquidity they provide reduces the price impact of trades (and therefore transaction prices are closer to true values).

We also examine the effect of a securities transaction (Tobin) tax on the behavior of these uninformed traders, and on the market more generally. Many countries impose a transaction tax in order to curb short term speculation, presumably the hallmark of noise traders, with the most recent being Thailand’s ill-fated attempt to do so in December 2006. Stiglitz [1989] conjectured that such a tax would work because it would be unlikely to discourage trading by those whose trades are motivated by private information or liquidity needs, and so would mainly serve to drive out the noise traders. Not surprisingly, we find that the transaction tax dramatically reduces trading volume. However, we find that the tax reduces activity by the uninformed traders and the informed traders roughly equally (contrary to the conjecture of Stiglitz [1989]), and perhaps as a result it does not alter bid-ask spreads or other price impact measures of liquidity, and has only a weak effect (if at all) on the informational efficiency of prices.

Taken together, our results suggest that the many literatures that consider the behavior of noise traders need to distinguish clearly between liquidity traders who trade for consumption and risk sharing and, hence, have rational liquidity needs, and “pure” uninformed traders who trade without information on their own volition and end up

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5 Arguments on the potential costs and benefits of a securities transaction tax can be found in Schwert and Seguin [1993] and Pollin, Baker, and Schaberg [2002].
creating excess noise in the market. Moreover, our results suggest that pure uninformed traders are likely to behave as “noise traders” by pursuing irrational contrarian strategies, rather than as skillful technical traders or rational liquidity providers. Such traders provide markets with costs (decreased efficiency) and benefits (increased liquidity for other traders) at their own expense. However, even if policy makers were to conclude that noise trading is undesirable, our results raise doubts that transaction taxes will provide much benefit.

Our study builds upon and extends several branches of the literature on laboratory markets. We start with a setting in which traders must aggregate information held by different traders, as in Plott and Sunder (1982, 1988) and a number of subsequent studies. As in Copeland and Friedman (1991), we examine markets with both informed and uninformed traders; however, while Copeland and Friedman focus on the how the behavior of the informed traders impounds their information into price, we focus on how the behavior of the uninformed traders might impede that process. Our manipulation of securities transaction taxes also extends the growing experimental literature on the effects of market design. For example, Bloomfield and O’Hara (1999) and Flood, Huisman, Koedijk, and Mahieu (1999) investigate the effects of transparency regimes on liquidity, Theissen (2000) compares volume and executions costs of different market structures (call auctions, continuous auctions, and dealer markets), and Ackert, Church, and Jayaraman (2001) examine the effects of imposing circuit breakers.

The rest of this paper is organized as follows. Section 2 sets out the experimental design. In Section 3 we present the results: we look at the trading strategies and profits of the uninformed traders, and after establishing that they introduce noise trading into the market, we analyze their impact on market liquidity and the informational efficiency of

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6 Our results are therefore related to the analysis in Bloomfield, Tayler and Zhou (2007) of contrarian and momentum strategists of informed and uninformed traders in robot-specialist markets (in which a robot sets prices at which traders can trade).

7 See also Lamoureux and Schnitzlein (1997, 2004) who look at the impact of competition, either across market structures or across dealers, on liquidity.
Section 4 summarizes our results and offers conclusions. There are also two Addenda to the paper available on the RFS web site. Addendum 1 provides a short background and review on the many ways noise trading has been viewed in the literature, while Addendum 2 makes available the instructions that were given to participants in the experiment and provides additional descriptive figures of the data gathered in our experimental markets.

2. The Experiment

We now describe our experimental setting and design, the trading task, and our participants’ training and incentives. As a useful preliminary, we note the following definitions. A cohort is a group of traders who always trade together. A security is a claim on a terminal dividend, and is identified by the liquidating dividend, distribution of information and liquidity targets (described below). A trading period is a 2-minute interval during which traders can take trading actions for a specific security. Only one security is traded in each trading period. Unless otherwise indicated, all prices, values, and winnings are denominated in laboratory dollars ($), an artificial currency that is converted into US currency at the end of the experiment.

2.1. Experimental Setting and Design

We create markets for the trading of securities. Each security pays a liquidating dividend equal to 50 plus the sum of five random numbers, each of which is uniformly distributed from –15 to 15. Values are truncated to lie in the range [0, 100], resulting in a roughly bell-shaped distribution.

Trader types are defined as follows. There are four informed traders in the market. Two informed traders observe the sum of the true liquidating dividend plus a predetermined random number (different for every security) drawn from the interval [–10, +10], while the other two observe the sum of the true liquidating dividend minus the same predetermined random number for that security. This structure guarantees that
each informed trader has imperfect information about the security value, so that price discovery requires the aggregation of disparate information as in the seminal experiments of Plott and Sunder (1982, 1988). The informed traders in the aggregate have perfect information, which simplifies the trading task (Lundholm [1991]), and guarantees that the rational expectations equilibrium price is equal to the true liquidating dividend.

There are four liquidity traders in the market. Liquidity traders are only told the prior distribution of dividends. As in Lamoreaux and Schnitzlein [1997] and Cason [2000], liquidity traders are assigned trading targets (in terms of number of shares) they must achieve before the end of trading. Failing to reach the target results in a penalty of $100 for each unfulfilled share. To limit their ability to speculate, liquidity traders are prohibited from closing out any positions they take on during trading. The liquidity targets are random, with two-thirds of the securities resulting in a non-zero aggregate net liquidity demand.

There may also be “uninformed traders” in the market. When present in the market, there are four uninformed traders; otherwise there are none. Uninformed traders have the same informational disadvantage of liquidity traders, but face no trading targets. They are free to pursue whatever trading strategies they desire. The behavior of these uninformed traders could fit the definition offered by Black [1986] of noise traders who may “simply like to trade”, but such uninformed trading could also be motivated by beliefs that they can make money by interpreting market information better than others.

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8 In other words, a liquidity trader with a target to “buy 20 shares” can only meet the target by buying 20 shares rather than, for example, by buying 30 shares and selling 10 shares. Falling short of the target or ending with more shares than the target prescribes results in a penalty.

9 For 8 securities, half of the liquidity traders must buy 20 shares and the other half must sell 30 shares, for an aggregate liquidity demand of −20. For another 8 securities, half of the liquidity traders must sell 20 shares, while the other half must buy 30 shares, for an aggregate liquidity demand of +20. The remaining eight securities have zero aggregate liquidity trader demand: for 4 of those securities, half of the traders must buy 20 shares and the other half must sell 20 shares; for the other 4 securities, half of the traders must buy 30 shares, and the other half must sell 30 shares.
or that they can earn profits by providing liquidity (due to the non-zero aggregate net
demand of the liquidity traders in two-thirds of the securities).\textsuperscript{10}

We also manipulate the transaction tax regime and the extremity of the realized
value of the security’s liquidating dividend. In the transaction tax regime, we impose a $2
tax on each side of every transaction. No taxes are assessed on trading when the
transaction tax regime is not in effect. The extremity factor (how different the realized
value of the security is from its unconditional mean) has two levels: High Extremity
(realized values that are at least $17 from expected value) and Low Extremity (realized
values that are no more than $16 from expected value). Extremity of the realized value of
the security is used as a measure of the value of the informed traders’ private
information; the farther away the security value is from its expected value, the more the
informed traders can profit from their information.

Our experiment manipulates factors both between cohorts and between securities
within each cohort (see Table 1 for the structure of the experiment). Our between-cohort
manipulations include trader composition and tax treatment order. Six cohorts are
composed of four informed traders and four liquidity traders, while the other six cohorts
are composed of four informed traders, four liquidity traders, and four uninformed
traders. Half of the cohorts of each composition trade in the presence of transaction taxes
during the first block of twelve securities (block 1) and then in their absence (block 2),
while the other half trade in the absence of transaction taxes during block 1 and in their
presence in block 2.

Our within-cohort manipulations include the value extremity and securities
transaction tax factors, which are crossed to allow for six securities in each cell of an
orthogonal 2 (tax regime) x 2 (value extremity) design within each cohort. All cohorts

\textsuperscript{10} Each trader knows his or her type, and each knows the populations of informed, liquidity, and
uninformed traders in the market. Traders do not know the roles played by specific participants in the
experiment.
trade the same twenty four securities. As detailed in footnote 8, securities also vary according to the aggregate net demand of the liquidity traders, which can be +20, –20 or 0. We balance aggregate net demand with our other factors by ensuring that there is no significant correlation of aggregate net demand with the other factors.\textsuperscript{11}

2.2. Trading

Each security is continuously traded for two minutes. Our double auction market is organized like a typical electronic limit order book where traders can enter buy or sell limit orders and the execution of limit orders follows strict price/time priority rules. Traders can execute outstanding limit orders in the book by clicking a “buy 1” button, which allows them to buy one share at the lowest current asking price, or by clicking a “sell 1” button, which allows them to sell one share at the highest current bid price. Executing a limit order in the book is equivalent to submitting a market (or marketable limit) order.

Limit orders must have integer prices between 0 and 100. Each order is instantaneously shown on all traders’ computer screens, indicating that an unidentified trader is willing to buy or sell one more share at the posted price. Traders can cancel their unexecuted limit orders at any time. Trades are reported immediately to all traders, indicating the price and the trade direction. The colorful, mouse-driven, graphical interface (nearly identical to that used in Bloomfield, O’Hara and Saar [2005], and shown in Figure 1), allows for very rapid trading, as traders need not use the keyboard to type in orders or cancellations, and can see at a glance whether market activity or the order book has changed. Traders can also continuously observe on the screen their current position (in terms of shares and cash), the number of shares they bought or sold, and the average price they paid for the shares they bought or sold.

\textsuperscript{11} A prior experiment indicates that realizations of aggregate net demand do not qualify the effects of taxes and value extremity on the behavior and impact of uninformed traders in a setting very similar to that examined here. Therefore, we expect this imperfect balancing technique to be adequate and allow clean inferences.
2.3. Participants, Training, and Incentives

The experiments were conducted in the Business Simulation Laboratory (BSL) at the Johnson Graduate School of Management at Cornell University, using a mixture of MBA and undergraduate students. All participants experienced intensive training for the experiment. Participants first attended a 90-minute training session, which began with 5-10 minutes in which traders could read the written instructions and 15-25 minutes of oral review of those instructions.\(^\text{12}\) The remaining time was devoted to allow participants to trade securities in each of the three roles (informed trader, liquidity trader, and uninformed trader) in markets of up to 20 traders. A total of 120 participants returned for a second session, which began with about 15 minutes of review (silent reading of instructions, review of key points, and one practice security). The remaining time was devoted to trading the 24 securities from which our data are drawn.

Traders started trading in each security with zero endowments of cash and shares. Unlimited negative cash and share balances were permitted, so traders could hold any inventory of shares they desired, including short positions.\(^\text{13}\) Traders were told that at the end of trading shares paid a liquidating dividend equal to their true value. A trader’s net trading gain or loss for a security would then equal the value of their final share holdings plus or minus their ending cash balance. Any penalties assessed to a liquidity trader for failing to hit a target are deducted from this trading gain or added to her trading loss. When applicable, transaction taxes are also subtracted from the trading profits or losses of traders.

Each participant was paid $60 plus or minus one dollar for every 1000 laboratory dollars gained or lost through trading, taxes and penalties, to a minimum of $5. This minimum was paid to only four of the 120 subjects, indicating that most traders likely did

\(^{12}\) The experimental instructions can be found in Addendum 2 to this paper that is posted on the RFS website.

\(^{13}\) The unlimited ability to short-sell balances the unlimited ability to borrow, eliminating the risk of price bubbles driven by excess cash in the market (as observed by Caginalp, Porter and Smith [2001]).
not engage in risk-seeking behavior due to the truncation of downside risk. Participants were told the explicit formula used to compute their winnings to ensure that they unambiguously understood the incentives in the experiment (and how these incentives relate to trading).

3. Results

In general, we find that all three trader types (informed, liquidity, and uninformed) trade using a mix of market and limit orders. This evidence suggests that participants in the experiment understood the market mechanism and felt comfortable pursuing various trading strategies. We also observe that our markets are “well-behaved” in that pricing errors tend to decline over the trading period, order flows and volume exhibit the usual patterns observed in prior studies, and spreads generally decrease over time.

Our experimental framework is designed to investigate whether unconstrained uninformed traders behave like noise traders, how they affect market outcomes, and how their influence and behavior is impacted by transaction taxes. Investigating these issues requires a thorough statistical analysis, and as a useful preliminary, we first discuss the statistical methodology we employ before turning to our results.

3.1 Statistical Analysis

We use repeated-measures ANOVA, which is a conservative and robust procedure for analyzing experimental data. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. This design reduces the problem, common in experimental economics, of overstating statistical significance by assuming that repetitions of the same actions by the same group of subjects are independent events.

Therefore, our statistical analysis for market-level variables (e.g., volume) has a 2 (noise) x 2 (extremity) x 2 (tax) factorial structure. The noise factor represents the presence of uninformed traders in the market and has two levels: Noise (in half of the
cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and No Noise (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). The securities transaction tax factor has two levels: Tax ($2 tax on the buying or selling of each share is imposed) and No Tax (no securities transaction tax is imposed).

For analyses of individual-level variables (such as order-submission rates), we first compute the dependent variable within each cell (defined by the appropriate factors) for each of the participants, and then average over the four traders of a certain type to get one number for each cohort that we can use in the ANOVA. Our statistical analysis for individual-level variables has a factorial structure of 2 (type) x 2 (extremity) x 2 (tax) for the cohorts with just two types of traders (informed and liquidity), or 3 (type) x 2 (extremity) x 2 (tax) for cohorts with three types of traders (informed, liquidity, and uninformed). In a few cases we also compute the variables of interest separately for ten 12-second time intervals within the trading period. For these variables we add another factor, time, to the ANOVA.

3.2 Strategies and Profits

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14 We repeated all the analyses testing for the influence of another factor: the order of the tax blocks in the experiment (i.e., whether participants first traded securities under the tax regime and then without taxes, or vice versa). In almost all cases the effect of this factor was not significant, and therefore we omit it from the presentation of the results. Section 3.3 discusses the only case where we have found that the order of the tax blocks mattered.

15 We present all statistically significant main effects and interactions from the repeated-measures ANOVA analysis in the tables and figures. A main effect examines the influence of one factor averaging over all the levels of the other factors. An interaction is when the effect of one factor is different at different levels of the other factors. In the text of the paper, we provide the \textit{p-value} for the main effects in parentheses without specifically mentioning the factor (it can be understood from the context of the sentence), while interactions are specifically stated in parentheses next to the \textit{p-values}. Lastly, in a few of instances where the variables under investigation can be either positive or negative (e.g., trading profit), we also provide in the tables indication of statistical significance against the hypothesis of a zero value using a \textit{t}-test.
As a first step to understanding the influence of our uninformed traders on markets, we investigate how they differ from liquidity traders, and whether they tend to be skillful technical traders, profitable liquidity providers, or irrational momentum or contrarian traders. We first consider their trading strategies, and in particular the taking rate of limit orders. The taking rate is defined as the number of shares a trader trades by submitting market orders divided by the total number of shares he trades (where the denominator consists of both market and executed limit orders). The higher the taking rate, the more the trader transacts by demanding rather than supplying liquidity. The taking rate also speaks to the aggressiveness or trading urgency (as opposed to patience) demonstrated by traders.

Figure 2 shows these taking rates by trader types in markets with and without uninformed traders. Looking first at markets without uninformed traders, we see that informed traders start by demanding more liquidity, and as time goes by they shift to supplying more liquidity. Liquidity traders conversely start by trying to trade more using limit orders (i.e., supplying liquidity) and then switch to market orders to make sure they meet their targets (type*time interaction \( p\text{-value} < 0.0001 \)). These effects mirror those found in Bloomfield, O’Hara and Saar [2005] who argue that the better information of the informed traders allows them to take on a more prominent market making role as trading progresses.

When uninformed traders are present, the behavior of the informed and liquidity traders remains approximately the same. However, our uninformed traders act very differently, particularly when compared to the liquidity traders: uninformed traders trade more by supplying liquidity (a lower taking rate) in the early stage of the market, and this tendency increases with time. Our results on trading strategies highlight the importance of separating liquidity trading from manifestations of uninformed trading that are not motivated by consumption or risk sharing. Such uninformed trading could play a far more
complex role than is envisioned in the traditional market microstructure models that specified exogenous liquidity demand.

In general, uninformed traders appear to trade using limit orders more than market orders, and they provide at least as much depth to the best bid and ask prices as the informed and liquidity traders. In fact, the average contribution of a typical uninformed trader to best bid or offer (BBO) depth is 1.01 shares, compared with 0.97 shares for an informed trader, and 0.96 for a liquidity trader (although these differences are not statistically significant). To determine whether this liquidity-providing behavior is rational, we turn to an examination of trading profits.

Panel A of Table 2 provides the gross trading profits of informed, liquidity, and uninformed traders (without taking into account the loss of money due to paying the tax). The table shows separately profits for high and low extremity securities, to enable examination of the significant interaction between trader type and extremity. As expected, informed traders make money and liquidity traders lose money. The effects are more pronounced when value extremity is high, reflecting the increased ability of informed traders to profit when the value of their information is higher. Some of these increased profits clearly come at the expense of the uninformed traders: Uninformed trader losses are much larger when extremity is high than when it is low, and are even greater than the liquidity traders’ losses. These results are clearly inconsistent with rationality—our unconstrained uninformed traders are not forced to trade, so they could improve their profits by not trading at all. Hence, they truly embody the definition of “noise traders” who trade for no rational reason and lose money on average. Moreover, the greater losses in extreme-value securities suggest that these traders are behavioral contrarians, rather than behavioral momentum traders.

16 While not including the effects of taxes, gross trading profit does take into account penalties that are assessed against liquidity traders who miss their targets. Panel B of Table 2 reports net trading profits that account for the effects of the securities transaction tax.
To provide direct evidence on the uninformed traders’ technical trading strategies, we analyze the measure CONTRA, which is defined as the number of orders the traders submitted when the recent price change (mid-quote return in the previous 10 seconds) was in the opposite direction to the order (e.g., negative or zero return when the trader buys) divided by the total number of orders. Table 3 presents our results. What may seem peculiar on first inspection is that even informed traders often trade in opposite direction to recent price movements. This could reflect the finding of Bloomfield, O’Hara, and Saar [2005] that informed traders often behave as market makers (who are contrarian by nature), especially when the value of their information is low. Such an interpretation is consistent with the observed pattern in Table 3 whereby informed traders behave in a much less contrarian fashion when the value of their information is high.

The table also demonstrates a strong contrarian tendency for the uninformed traders, whom we now identify with technical noise traders. This result echoes empirical findings in the U.S. and other countries that individual investors tend to exhibit contrarian trading strategies (see Kaniel, Saar and Titman [2006] for evidence and a discussion of the literature). Thus, when prices are moving up the uninformed traders are more likely to submit sell orders, and conversely submitting buy orders after the market is moving down.

This strategy can potentially work well in term of earning small profits by providing liquidity when the underlying value of the security is stable. But this is exactly the wrong strategy when security prices are adjusting to valuable new information. In particular, our results indicate that there is a statistically significant interaction of type and extremity ($p$-value $< 0.0001$). Thus, when extremity is high, informed traders naturally act in a much less contrarian manner, and their CONTRA measure decreases from 0.66 to 0.52. Such behavior is sensible as the informed are moving prices toward the true value, and their continued trading in that direction exhibits a greater momentum component. In contrast, we see almost no change in the uninformed traders’ strategies.
(0.66 when extremity is low and 0.68 when it is high). Thus, the uninformed traders are increasingly taking the other side of the informed traders’ trades, a behavioral strategy that produces extensive losses for these noise traders and has the potential to reduce efficiency for the market.

### 3.3 Market Liquidity

Having established that the uninformed traders in our experiment generate noise trading, we proceed to investigate how this noise trading affects market liquidity as captured by volume, depth, and measures of transactions costs (spreads and the price impact of market orders).

#### 3.3.1 Volume

As expected, the amount of trading in the market is significantly influenced by the inclusion or exclusion of the uninformed traders, and by the presence or absence of a transaction tax. Panel A of Table 4 shows that volume is on average about 61% greater in securities where the uninformed traders are present \( (p\text{-value} = 0.0053) \), and volume is on average about 20% lower in securities traded under the tax regime \( (p\text{-value} = 0.0140) \). The results also show that there is a significant interaction between extremity and noise trading: volume is higher for high extremity securities only when there are uninformed traders in the market. This finding suggests that the uninformed traders are more active when security prices appear to be farther away from their expected values, consistent with their acting as behavioral traders who fail to protect themselves from the adverse selection that arises when security values are extreme.

Panel B of Table 4 shows that adding the uninformed traders to a market enables informed traders to increase their trading activity by on average about 28% while the amount of trading by the liquidity traders is unaffected (because they are constrained to trade the same number of shares in all cells of the design). Perhaps more intriguing is what happens to trading activity when a securities transaction tax is imposed. In the absence of uninformed traders, informed traders trade on average 25% fewer shares when
taxes are imposed, while liquidity traders, with their exogenous trading requirements, are little affected (type*tax \( p\)-value = 0.017). When uninformed traders are present in the market we observe a similar picture: informed trading falls by 28% on average. The uninformed traders, who are not constrained to trading a target like the liquidity traders, also show a marked decline in activity (by 23% on average) in the presence of taxes.\(^{17}\) These results suggest that the uninformed traders believe that they have the ability to infer very useful information from market data, or else they would have been deterred by Tobin taxes more than the informed traders.

### 3.3.2 Depth

Another dimension of market liquidity is displayed liquidity in the limit order book. Table 5 provides data on average depth at the best bid-or-offer (BBO) prices, which we use as a measure of displayed liquidity.\(^{18}\) We find that noise trading generated by the presence of uninformed traders dramatically increases depth, both in the tax and no-tax settings, by on average 89% (\( p\)-value = 0.0009). In the no-tax setting, adding the uninformed traders doubles the depth at the best bid or offer prices, suggesting that these traders are actively submitting limit orders that match or better the BBO. We also observe that greater adverse selection, which we measure by the value of the informed traders’ private information (the extremity manipulation), reduces depth (\( p\)-value = 0.0019), inline with the hypothesized impact of information asymmetry in the market microstructure literature. An interaction of noise trading, extremity, and taxes shows that while taxes

\(^{17}\) The significant type*tax interaction that we report in Table 4 implies that informed and uninformed traders indeed trade less under the tax regime (because the statistical test compares them to the liquidity traders who, by construction, trade the same number of shares). A statistical test that excludes the liquidity traders shows that transaction taxes affect the willingness to trade of informed and uninformed traders about the same (type*tax interaction \( p\)-value = 0.3548).

\(^{18}\) Looking at BBO depth has a few advantages over analyzing total depth in the book. Total depth is influenced by stale limit orders: when market prices are running away from a trader’s limit orders, the trader would often submit more aggressive limit order but would not necessarily bother to cancel stale orders. Also, traders would submit limit orders away from current prices in an attempt to game other participants to believe that the true value resides elsewhere. We want a measure of displayed liquidity that represents actual commitments of traders, and BBO depth seems a particularly appropriate measure for this purpose (see also Bloomfield, O’Hara and Saar [2005]).
tend to decrease depth in the book, this need not always occur (noise*extremity*tax $p$-value = 0.0046).

### 3.3.3 Spreads and Price Impact

We look at two measures of transactions costs in our markets: spreads and price impact of market orders. In general, spreads exhibit the usual shape in that they start high and decline throughout the trading period until the very end, when they increase slightly. This end-of-period effect is due to the increased use of market orders by liquidity traders (who have to trade) coupled with the cancellation of limit orders by liquidity traders who have reached their trading targets (see Bloomfield, O’Hara and Saar [2005] for a discussion of these effects). To examine the behavior of spreads over the trading period, we divide the trading period into ten time intervals and compute time-weighted spreads separately for each interval. Figure 3 shows the behavior of spreads over time.

The data reveal a significant noise*extremity*time interaction ($p$-value = 0.0304), so we analyze the behavior of spreads across four experimental regimes: Low Noise (i.e., no uninformed traders) / Low Extremity (LNLE); Low Noise / High Extremity (LNHE); High Noise (i.e., uninformed traders are present) / Low Extremity (HNLE); High Noise / High Extremity (HNHE). The data do not indicate any tax interactions, so we do not segment the results according to tax regimes.

Market microstructure models suggest that spreads will be affected by the extent of asymmetric information, which in our model is partially captured by the extremity variable that represents the value of the private information. As expected, we observe an extremity effect consistent with predictions of market microstructure models. Our main interest is in how noise trading influences these spreads. The data clearly indicate that when our uninformed traders are present, spreads are lower. In Figure 3 the bottom two lines correspond to spreads with noise trading (i.e., when uninformed traders are present in the market), and these almost always lie below the spreads in markets without noise trading. Closing spreads (not reported) are also lower when the uninformed traders are
Notice that this result is similar in principle to the predicted effect of (exogenous) liquidity traders in market microstructure models (e.g., Glosten and Milgrom [1985]), where liquidity traders are shown to affect the permanent price impact of market orders (and hence the spread).

To gain more insight into how the uninformed traders are affecting the market, we decompose the price impact of market orders into temporary and permanent price impacts (attributed to liquidity provision and information, respectively). This type of decomposition is often used in the empirical market microstructure literature. For a market order placed at time $t$ denote the transaction price by $P_t$, the midpoint between the best bid and offer prices in the limit order book (just before the trade) by $M_t$, and the midpoint between the best bid and offer prices prevailing five trades after the market order for which we are computing the price impact by $M_{t+5}$. The total price impact for a buy (sell) order is defined by $P_t - M_t (M_t - P_t)$. The permanent price impact for a buy (sell) order is defined by $M_{t+5} - M_t (M_t - M_{t+5})$ and the temporary price impact is defined by $P_t - M_{t+5} (M_{t+5} - P_t)$. Note that the total price impact is the sum of the permanent and temporary components.

Figure 4 shows that the price impact measures are greatly affected by the presence of noise trading, with the most visually striking effect being the significantly lower temporary price impact when there are uninformed traders in the market ($p$-value = 0.0312). For example, the total price impact in low extremity securities is $3.38, which is comprised of $2.93 in temporary price impact and $0.45 in permanent price impact. Both of these components are lower when the uninformed traders are present in the market, with the temporary price impact dropping 49% to $1.49 and the permanent price impact dropping 38% to $0.28.

---

19 Closing spreads (the spread in the limit order book at the end of trading) also exhibit a significant noise*extremity interaction ($p$-value = 0.0426) and these closing spreads are lower when there are uninformed traders in the market.
What the figure makes clear, however, is that the magnitude of the decrease in total price impact is driven mainly by the decrease in temporary price impact. In low extremity securities, the total price impact decreases by 48% to $1.76. This decrease of $1.62 (from $3.38 to $1.76) consists of a $1.44 reduction in temporary price impact and a $0.18 reduction in permanent price impact. In other words, about 89% of the reduction in total price impact can be attributed to the decrease in temporary price impact. For high extremity securities, 77% of the reduction in total price impact when uninformed traders are in the market can be attributed to the decrease in temporary price impact.

This evidence suggests that the uninformed traders do make the market more liquid, and in particular their activity lessen reversals due to illiquidity. Therefore, their most significant influence on the total price impact of market orders seems to come from additional risk-averse provision of liquidity that lowers the temporary price impact (as in the models of Grossman and Miller [1988] and Campbell, Grossman, and Wang [1993]) rather than from lowering the permanent price impact (as the exogenous liquidity traders do in Glosten and Milgrom [1985] and Kyle [1985]).

While in principle this finding could have been consistent with our uninformed traders acting either as rational liquidity providers or as behavioral contrarian traders, our findings of significant trading losses in Section 3.2 rule out rational liquidity provision and suggest that irrational contrarian traders can have an important effect on market liquidity. We do not find evidence that informed traders completely offset the effects of noise trading as predicted by Kyle [1985]. We also do not find a significant effect of taxes on spreads, although taxes do dramatically reduce volume. The securities transaction tax does seem to limit the activity of the uninformed traders, but also affects the informed traders, consistent with the models of Subrahmanyam [1998] and Dow and Rahi [2000], resulting in not much change in the price impact measures.

3.3 Informational Efficiency
The informational efficiency of a market refers to how well, and how quickly, market prices reflect true values. There are several ways to measure such efficiency, but perhaps the most straightforward manner is to consider pricing errors, or the average gap (in absolute value) between transactions prices and the true value of the liquidating dividend, which we denote by $\text{DEVP}$. Figure 5 demonstrates that pricing errors decline throughout the trading period (from time interval 1 to 10) as prices incorporate more of the informed traders’ information. There is also a significant interaction of extremity*time ($p$-value < 0.0001): pricing errors for high extremity securities start much higher and converge in a more dramatic fashion. Pricing errors for low extremity securities naturally start smaller (as prices at the beginning are closer to the prior expected value of 50), but they also decrease with time on average.\footnote{While Figure 5 shows that the decline for low extremity securities is much smaller in magnitude that the decline for high extremity securities, analysis of ANOVA simple effects reveals a statistically significant decline for $\text{DEVP}$ in each of our noise*extremity cells.}

Does noise trading introduced by the uninformed traders in our experiment reduce the market’s informational efficiency? Table 6 provides evidence on this issue. For high extremity securities, this effect is evident: the presence of uninformed traders (who are not required to trade) increases the pricing errors in both the tax and no-tax regimes by 22\% on average. However, for low extremity securities, this effect is not found. Adding noise trading to these markets does not increase pricing errors, but rather decreases them by about 16\% ($\text{noise*extremity } p$-value $= 0.0262$).

Since the uninformed traders add more liquidity to a market, it is possible that the small decrease in pricing errors we observe in low extremity securities comes simply from smaller spreads. To examine this possibility, we look at a different definition of pricing errors, $\text{DEVMID}$, computed as the distance of the true value from the prevailing mid-quote when a transaction occurs. We find that $\text{DEVMID}$ pricing errors for low extremity securities are about the same with and without the uninformed traders (4.5 and...
4.4, respectively). This is consistent with our conjecture that the lower DEVP pricing errors for low extremity securities are due to better liquidity (and lower spreads). However, the influence of uninformed traders on pricing errors computed from mid-quotes in high extremity securities is similar to that found with DEVP: noise trading worsen informational efficiency when there is more information in the market. We interpret this evidence as suggesting that these traders worsen the informational efficiency of the market exactly when it is most important (i.e., when the value of new information is large).

The analysis of DEVP and DEVMID provides one of the more interesting results of our experiment in that it shows why the damaging influence of noise trading on the informational efficiency of prices is not always observed. The key to understanding this results lies in evidence we present that the activity of the uninformed traders improves market liquidity, and in particular, reduces the temporary price impact of trades. When adverse selection in the market is low, improved liquidity means that transaction prices are closer to true values (because the price impact of trades is smaller). When adverse selection in the market is high, however, the detrimental effects of the uninformed trader’s contrarian strategies dominate and noise trading unequivocally harms the adjustment of prices toward fundamental values.

It is interesting that there is no statistically significant effect of the securities transaction tax on the pricing errors measures DEVP and DEVMID. We find a small effect when we look at pricing errors computed from end-of-period prices, but we are reluctant to place too much confidence in this result for two reasons. First, it appears only in one of the three pricing errors measures. Second, this it is also the only measure in the entire experiment where we observe a tax order effect (i.e., that the result is different
depending on whether participants first traded securities under the tax regime and then without taxes, or vice versa).\textsuperscript{21}

An alternative approach to evaluating informational efficiency is to consider how the actions of individual traders contribute to value discovery, or the evolution of transaction prices toward the true value of the security. To compute the measure INFEFF, we assign +1 or –1 to each executed order in the following manner. If the true value is higher than the price, we assign +1 to a buy order of a trader that resulted in a trade and –1 to a sell order that resulted in a trade. If the true value is lower than the price, we assign –1 (+1) to a buy (sell) order of a trader that resulted in a trade. The measure is then aggregated for all market and executed limit orders of a trader and divided by the number of his trades (the measure is therefore always in the range [−1, +1]). The more positive (negative) INFEFF of a trader, the more his trades contribute to (interfere with) value discovery.

Table 7 shows, not surprisingly, that informed traders help prices converge to true values, while liquidity traders hinder this effect (as predicted by market microstructure models). The uninformed traders affect the market differently depending upon the degree of adverse selection. When there is not much adverse selection (value extremity is low), noise trading does not interfere much with value discovery (−0.04 for the uninformed traders, which is not statistically different from zero, as opposed to −0.13 for the liquidity traders). When the value of information is high, uninformed traders greatly hinder value discovery (−0.35 for the uninformed traders as opposed to −0.20 for the liquidity traders). These results further show that our unconstrained uninformed traders behave differently

\textsuperscript{21} In sessions where traders start without taxes and then taxes are imposed, transaction taxes seem to bring about a decrease in price errors computed from end-of-period prices from 6.87 to 4.63 (tax*order interaction \textit{p-value} = 0.0253). One possible explanation for this interaction is that taxes improve efficiency only when traders have already gained extensive experience in the markets, though we do not find similar experience effects in other variables.
from the liquidity traders (who must trade), and therefore have a different impact on the market, which justifies looking at these two types of traders separately.

4. How Noise Traders Matter

The term ‘noise trader’ has a variety of contradictory meanings in finance. We construct an experimental setting that clearly distinguishes between two of these meanings by including “liquidity traders” who trade because they face random liquidity shocks, and “uninformed traders” who may choose to trade despite having no informational advantages or exogenous motivations for trade.

The first contribution of our paper is to examine the behavior and influence of these uninformed traders, who trade for reasons other than liquidity or risk sharing needs. We find no evidence that these uninformed traders provide liquidity to the market in a profitable fashion (like dealers would) or exploit slow-moving traders (like “SOES bandits” would). Instead, these traders pursue aggressive and unprofitable contrarian strategies, and hence simply generate “noise” trading. In so doing, these uninformed traders increase market volume and liquidity, but reduce the ability of the market to react to new information. Much as predicted in the behavioral finance literature, noise traders trade too much and too often in ignorance.\(^{22}\)

A second contribution of our paper is the analysis of a securities transaction tax, and in particular the question of whether such taxes are desirable. If the goal of such a tax is simply to limit noise trading, then our results provide some backing for this approach. But these taxes have other effects as well, and in particular they also reduce the trading and profitability of informed traders. Indeed, this difficulty underscores a general concern with the unfocused nature of such taxes; while their goal may be to affect particular traders, the incidence of the tax falls on every market participant. On balance,

\(^{22}\) See Odean [1999] for more evidence of these effects.
our results raise doubts that securities transaction taxes will provide much benefit. More targeted approaches, such as the SEC’s minimum wealth requirements for day traders, may be a more effective strategy to limit particular types of noise trading in markets.23

How then to consider the role of noise traders in financial markets? Our findings show that noise traders do introduce complex effects into market behavior. Some of these effects are positive: noise traders generally reduce spreads and the temporary price effects of trades, allowing liquidity traders to reduce their losses when noise traders are present. Other effects are more decidedly negative: they tend to hinder adjustment of prices to the true value most when the market is least efficient. Of particular importance is that the noise trader behavior we document is not the same as the behavior we observe for the liquidity traders who must trade. This suggests that the simple view of noise trading underlying market microstructure models may be flawed: noise traders are not simply liquidity traders, and modeling their differing behavioral motivations may be a fruitful direction for microstructure research.

23 We caution, however, that our analysis is not general enough to provide overall conclusions on securities transaction taxes. We do not, for example, allow such taxes to influence the portfolio-based liquidity traders’ participation decisions, although such effects are likely to be significant. Should liquidity traders opt not to participate in markets with securities transaction taxes, risk sharing and allocational efficiency in the economy would suffer, and market performance would almost surely be degraded. For a discussion of the issues surrounding participation effects and securities transaction taxes see O’Hara [2004].
References


Table 1
Experimental Design

Data are drawn from twelve cohorts. As shown in Panel A, six cohorts include eight traders each (four informed traders and four liquidity traders) and six cohorts include twelve traders each (four informed traders, four liquidity traders, and four uninformed traders). Cohorts also vary according to whether they traded with transaction taxes in the first block of twelve securities or the second block of twelve securities. All cohorts traded 24 securities in a balanced 2x2 factorial design shown in Panel B, with factors for the transaction tax and security value extremity. The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). The securities transaction tax factor has two levels: Tax ($2 tax on the buying or selling of each share is imposed) and No Tax (no securities transaction tax is imposed). To account for any possible order effects in the presentation of the securities transaction tax, half of the cohorts of each size traded with transaction taxes in the first set of 12 securities (block 1), while the other half traded with transaction taxes in the second set of 12 securities (block 2). Within each block of twelve securities, securities were presented in a predetermined random order that was the same for all cohorts.

Panel A: Between-Cohort Experimental Design

<table>
<thead>
<tr>
<th>Cohort</th>
<th>Traders Included</th>
<th>Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4 informed, 4 liquidity</td>
<td>Taxes in Block 1</td>
</tr>
<tr>
<td>2</td>
<td>4 informed, 4 liquidity</td>
<td>Taxes in Block 1</td>
</tr>
<tr>
<td>3</td>
<td>4 informed, 4 liquidity</td>
<td>Taxes in Block 1</td>
</tr>
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<td>4 informed, 4 liquidity</td>
<td>Taxes in Block 2</td>
</tr>
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<td>6</td>
<td>4 informed, 4 liquidity</td>
<td>Taxes in Block 2</td>
</tr>
<tr>
<td>7</td>
<td>4 informed, 4 liquidity, 4 uninformed</td>
<td>Taxes in Block 1</td>
</tr>
<tr>
<td>8</td>
<td>4 informed, 4 liquidity, 4 uninformed</td>
<td>Taxes in Block 1</td>
</tr>
<tr>
<td>9</td>
<td>4 informed, 4 liquidity, 4 uninformed</td>
<td>Taxes in Block 1</td>
</tr>
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<td>10</td>
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</tr>
<tr>
<td>11</td>
<td>4 informed, 4 liquidity, 4 uninformed</td>
<td>Taxes in Block 2</td>
</tr>
<tr>
<td>12</td>
<td>4 informed, 4 liquidity, 4 uninformed</td>
<td>Taxes in Block 2</td>
</tr>
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### Panel B: Between-Security Experimental Design

<table>
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<td>12</td>
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<tr>
<td>1</td>
<td>1</td>
<td>Low</td>
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<tr>
<td>8</td>
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<td>Low</td>
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<td>22</td>
<td>2</td>
<td>Low</td>
</tr>
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</table>
Table 2  
Trading Profits

This table presents evidence on trading profits of the three trader types. In Panel A we provide gross trading profit (profit or loss incurred by trading, including penalties assessed against liquidity traders who did not meet their targets), where we do not subtract from the trading profit or loss the securities transaction tax paid by the traders. In Panel B we provide net trading profit, which shows the “bottom line” profit or loss of a trader where transaction taxes are subtracted from securities traded under the tax regime. The numbers are provided separately for each cell in the (trader type) x (extremity) x (tax) factorial design. The trader type factor has three levels in half of the cohorts (informed traders, liquidity traders, and uninformed traders) and two levels in half of the cohorts (informed and liquidity traders only). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). The securities transaction tax factor has two levels: Tax ($2 tax on the buying or selling of each share is imposed) and No Tax (no securities transaction tax is imposed). Our statistical analysis relies on repeated-measures ANOVA. For analyses of individual-level variables (such as profit), we first compute the variable under investigation for an individual trader and then the average for a trader type within each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis. We also carry out \( t \)-tests of the hypothesis that profit (or loss) in each cell is different from zero. To present significance levels of these tests for each number in the table, we use ** to indicate significance at the 1% level and * to indicate significance at the 5% level (both against a two-sided alternative).

### Panel A: Gross Profit for each Trader Type

<table>
<thead>
<tr>
<th></th>
<th>Gross Profit</th>
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<th>Noise</th>
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<td><strong>No Tax</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Low Extremity</td>
<td>30.62</td>
<td>-30.62*</td>
<td>78.33**</td>
</tr>
<tr>
<td>High Extremity</td>
<td>100.67**</td>
<td>-100.67**</td>
<td>199.28**</td>
</tr>
<tr>
<td><strong>Tax</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Low Extremity</td>
<td>32.60</td>
<td>-32.60</td>
<td>78.92**</td>
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<tr>
<td>High Extremity</td>
<td>79.69**</td>
<td>-79.69**</td>
<td>178.35**</td>
</tr>
</tbody>
</table>

ANOVA results of sessions w/o Uninformed Traders (No Noise):
- Type  \( p \)-value<0.0001
- Type*Extremity  \( p \)-value<0.0001

ANOVA results of sessions with Uninformed Traders (Noise):
- Type  \( p \)-value<0.0001
- Type*Extremity  \( p \)-value=0.0038
Panel B: Net Profit for each Trader Type

<table>
<thead>
<tr>
<th>Net Profit</th>
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<th>Noise</th>
<th></th>
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<td>Informed</td>
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</tr>
<tr>
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<td>-100.67**</td>
<td>199.28**</td>
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<td>-128.87**</td>
<td>127.53**</td>
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</table>

ANOVA results of sessions w/o Uninformed Traders (No Noise):
- Type: p-value<0.0001
- Tax: p-value=0.0009
- Type*Extremity: p-value<0.0001

ANOVA results of sessions with Uninformed Traders (Noise):
- Type: p-value<0.0001
- Tax: p-value=0.0046
- Type*Extremity: p-value=0.0040
Table 3
Trading Strategies: Contrarian Trading

This table presents evidence on the extent of contrarian trading pursued by the different trader types. To compute the measure CONTRA, we look at the mid-quote return in the 10 seconds prior to each order a trader submits. We then calculate the measure CONTRA to be the number of orders the traders submitted when the recent price change was in the opposite direction to the order (e.g., negative or zero return when the trader buys) divided by the total number of orders. The numbers are provided separately for each cell in the (trader type) x (extremity) factorial design. The trader type factor has three levels in half of the cohorts (informed traders, liquidity traders, and uninformed traders) and two levels in half of the cohorts (informed and liquidity traders only). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). Our statistical analysis relies on repeated-measures ANOVA. For analyses of individual-level variables (such as CONTRA), we first compute the variable under investigation for an individual trader and then the average for a trader type within each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis. We do not provide a breakdown by the tax factor since there were no statistically significant interactions or a main effect for this factor.

<table>
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<tr>
<td>High Extremity</td>
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<td>0.59</td>
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ANOVA results of sessions w/o Uninformed Traders (No Noise):
- Extremity  p-value=0.0525
- Type*Extremity  p-value=0.0556

ANOVA results of sessions with Uninformed Traders (Noise):
- Type  p-value=0.0029
- Extremity  p-value<0.0001
- Type*Extremity  p-value<0.0001
Table 4
Liquidity: Trading Volume

This table presents findings on trading volume and the number of shares traded by each trader type. Panel A presents average market-wide trading volume in a security. The numbers are provided separately for each cell in the 2 (noise) x 2 (extremity) x 2 (tax) factorial design. The noise factor represents the presence of uninformed traders in the market and has two levels: Noise (in half of the cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and No Noise (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). The securities transaction tax factor has two levels: Tax ($2 tax on the buying or selling of each share is imposed) and No Tax (no securities transaction tax is imposed). Our statistical analysis relies on repeated-measures ANOVA. For analyses of market-level variables, such as volume, we judge statistical significance by computing the average of the dependent variable within each cell (defined by the appropriate factors) for each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis. Panel B presents the average number of shares traded by each trader type (uninformed, liquidity, and informed). We provide a breakdown by the type and tax factors only since there were no statistically significant interactions or a main effect for the extremity factor. For analyses of individual-level variables (such as the number of shares traded), we first compute the variable under investigation for an individual trader and then the average for a trader type within each of the cohorts. The numbers in the table represent the averages across the cohorts.

Panel A: Market-Wide Trading Volume

<table>
<thead>
<tr>
<th></th>
<th>No Tax</th>
<th>Tax</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Noise</td>
<td>Noise</td>
</tr>
<tr>
<td>Low Extremity</td>
<td>109.67</td>
<td>167.00</td>
</tr>
<tr>
<td>High Extremity</td>
<td>101.39</td>
<td>200.48</td>
</tr>
</tbody>
</table>

ANOVA results:

- Noise: \( p\text{-value}=0.0053 \)
- Tax: \( p\text{-value}=0.0140 \)
- Noise*Extremity: \( p\text{-value}=0.0158 \)

Panel B: Number of Shares Traded by each Trader Type

<table>
<thead>
<tr>
<th>Shares</th>
<th>No Tax</th>
<th>Tax</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Informed</td>
<td>Liquidity</td>
</tr>
<tr>
<td>No Tax</td>
<td>27.49</td>
<td>25.27</td>
</tr>
<tr>
<td>Tax</td>
<td>20.66</td>
<td>24.98</td>
</tr>
</tbody>
</table>

ANOVA results of sessions w/o Uninformed Traders (No Noise):

- Tax: \( p\text{-value}=0.0097 \)
- Type*Tax: \( p\text{-value}=0.0170 \)

ANOVA results of sessions with Uninformed Traders (Noise):

- Tax: \( p\text{-value}=0.0004 \)
- Type*Tax: \( p\text{-value}=0.0175 \)
Table 5
Liquidity: Depth at the Best Bid or Offer

This table presents results on average depth (in number of shares) at the best bid or offer prices in the limit order book (depBBO). The numbers are provided separately for each cell in the 2 (noise) x 2 (extremity) x 2 (tax) factorial design. The noise factor represents the presence of uninformed traders in the market and has two levels: Noise (in half of the cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and No Noise (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). The securities transaction tax factor has two levels: Tax ($2 tax on the buying or selling of each share is imposed) and No Tax (no securities transaction tax is imposed). Our statistical analysis relies on repeated-measures ANOVA. For analyses of market-level variables, such as depBBO, we judge statistical significance by computing the average of the dependent variable within each cell (defined by the appropriate factors) for each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis.

<table>
<thead>
<tr>
<th></th>
<th>No Tax</th>
<th></th>
<th>Tax</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Noise</td>
<td>Noise</td>
<td>No Noise</td>
<td>Noise</td>
</tr>
<tr>
<td>Low Extremity</td>
<td>6.21</td>
<td>13.51</td>
<td>5.88</td>
<td>9.76</td>
</tr>
<tr>
<td>High Extremity</td>
<td>5.09</td>
<td>8.25</td>
<td>4.45</td>
<td>9.44</td>
</tr>
</tbody>
</table>

ANOVA results:

- Noise  p-value=0.0009
- Extremity  p-value=0.0019
- Extremity*Tax  p-value=0.0095
- Noise*Extremity*Tax  p-value=0.0046
Table 6
Informational Efficiency: Average Pricing Errors

This table presents results on average pricing errors, DEVP, computed as the average over all transaction prices in a trading period of the absolute value of the difference between the transaction price and the true value. The numbers are provided separately for each cell in the 2 (noise) x 2 (extremity) x 2 (tax) factorial design. The noise factor represents the presence of uninformed traders in the market and has two levels: Noise (in half of the cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and No Noise (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). The securities transaction tax factor has two levels: Tax ($2 tax on the buying or selling of each share is imposed) and No Tax (no securities transaction tax is imposed). Our statistical analysis relies on repeated-measures ANOVA. For analyses of market-level variables, such as DEVP, we judge statistical significance by computing the average of the dependent variable within each cell (defined by the appropriate factors) for each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis.

<table>
<thead>
<tr>
<th></th>
<th>No Tax</th>
<th></th>
<th>Tax</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Noise</td>
<td>Noise</td>
<td>No Noise</td>
<td>Noise</td>
</tr>
<tr>
<td>Low Extremity</td>
<td>5.14</td>
<td>4.20</td>
<td>5.95</td>
<td>5.11</td>
</tr>
<tr>
<td>High Extremity</td>
<td>8.03</td>
<td>10.19</td>
<td>7.99</td>
<td>9.36</td>
</tr>
</tbody>
</table>

ANOVA results:
- Extremity, p-value<0.0001
- Noise*Extremity, p-value=0.0262
Table 7
Informational Efficiency: Value Discovery

This table presents evidence on the contribution of a trader type to value discovery, or whether the traders’ trades move prices closer to or away from the true value. To compute the measure INFEFF, we first assign +1 or –1 to each executed order in the following manner. If the true value is higher than the price, we assign +1 to a buy order of a trader that resulted in a trade and –1 to a sell order that resulted in a trade. If the true value is lower than the price, we assign –1 (+1) to a buy (sell) order of a trader that resulted in a trade. The measure is then aggregated for all market and executed limit orders of a trader and divided by the number of his trades (the measure is therefore always in the range [−1, +1]). The more positive (negative) INFEFF of a trader, the more his trades contribute to (interfere with) value discovery. The numbers are provided separately for each cell in the (trader type) x (extremity) factorial design. The trader type factor has three levels in half of the cohorts (informed traders, liquidity traders, and uninformed traders) and two levels in half of the cohorts (informed and liquidity traders only). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17 from the expected value) and Low Extremity (realized values that are no more than $16 from the expected value). Our statistical analysis relies on repeated-measures ANOVA. For analyses of individual-level variables (such as INFEFF), we first compute the variable under investigation for an individual trader and then the average for a trader type within each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis. We do not provide a breakdown by the tax factor since there were no statistically significant interactions or a main effect for this factor. We also carry out t-tests of the hypothesis that INFEFF in each cell is different from zero. To present significance levels of these tests for each number in the table, we use ** to indicate significance at the 1% level and * to indicate significance at the 5% level (both against a two-sided alternative).

<table>
<thead>
<tr>
<th>INFEFF</th>
<th>No Noise</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Informed</td>
<td>Liquidity</td>
</tr>
<tr>
<td>Low Extremity</td>
<td>0.33**</td>
<td>-0.13**</td>
</tr>
<tr>
<td>High Extremity</td>
<td>0.44**</td>
<td>-0.28**</td>
</tr>
</tbody>
</table>

ANOVA results of sessions w/o Uninformed Traders (No Noise):
Type p-value < 0.0001
Type*Extremity p-value = 0.0069

ANOVA results of sessions with Uninformed Traders (Noise):
Type p-value < 0.0001
Extremity p-value = 0.0388
Type*Extremity p-value < 0.0001
Figure 1
Example of a Trading Screen

This figure presents a screen snapshot for a practice security. The screen includes two graphs showing market activity. The left side of each graph shows every price at which an order has been posted (shown in green for the highest bid and lowest ask price, and yellow for other prices), and the number of shares posted at that price (shown by the number to the left of the graph). The right side of each graph shows every price at which the trader has personally posted an order, and the number of shares that the trader has posted at that price. The center of each graph also includes a solid green line indicating the highest bid or lowest ask entered by any trader, and a solid red line indicating the highest bid or lowest ask entered by that particular trader. This trader has entered the lowest ask (along with five other asks at the same price), but another trader has entered the highest bid.
Figures 2
Trading Strategies: Taking Rates of Limit Orders

In this set of figures we present the taking rates of limit orders by the different trader types over the trading period. The Taking Rate is defined as the number of shares a trader trades by submitting market orders divided by the total number of shares he trades (where the denominator consists of both market and executed limit orders). The higher the taking rate, the more the trader transact by demanding rather than supplying liquidity. The Taking Rate also speaks to the aggressiveness or trading urgency (as opposed to patience) demonstrated by traders. To examine the behavior of the taking rate over the trading period, we divide the trading period into ten time intervals and compute the taking rate separately in each interval. The data reveal a significant type*time interaction, so we present the results separately for each cell in the (trader type) x (time intervals) factorial design. The trader type factor has three levels in half of the cohorts (informed traders, liquidity traders, and uninformed traders) and two levels in half of the cohorts (informed and liquidity traders only). The data do not indicate any tax or extremity interactions or main effects, so we do not segment the results according to these factors. We present two side-by-side figures: one for the cohorts without uninformed trader participation and one for the cohorts with uninformed traders. Our statistical analysis relies on repeated-measures ANOVA. For analyses of individual-level variables (such as the taking rate), we first compute the variable under investigation for an individual trader and then the average for a trader type within each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis.

ANOVA results of sessions w/o Uninformed Traders (No Noise):
- Time p-value=0.0426
- Type*Time p-value<0.0001

ANOVA results of sessions with Uninformed Traders (Noise):
- Time p-value=0.0049
- Type p-value<0.0001
- Type*Time p-value<0.0001
This figure shows time-weighted spreads between the best bid and ask (a.k.a. offer) prices in the limit order book over the trading period. To examine the behavior of spreads over the trading period, we divide the trading period into ten time intervals and compute time-weighted spreads separately in each interval. The data reveal a significant noise\*extremity\*time interaction, so we present the results separately for each cell in the 2 (noise) x 2 (extremity) x 10 (time intervals) factorial design. The noise factor represents the presence of uninformed traders in the market and has two levels: HN (in half of the cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and LN (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity or HE (realized values that are at least $17 from the expected value) and Low Extremity or LE (realized values that are no more than $16 from the expected value). We graph the behavior of spreads over time for four cells: Low Noise (i.e., no uninformed traders) / Low Extremity (LNLE); Low Noise / High Extremity (LNHE); High Noise (i.e., uninformed traders are present) / Low Extremity (HNLE); High Noise / High Extremity (HNHE). The data do not indicate any tax interactions (or a main effect), so we do not segment the results according to tax regimes. Our statistical analysis relies on repeated-measures ANOVA. For analyses of market-level variables, such as spreads, we judge statistical significance by computing the average of the dependent variable within each cell (defined by the appropriate factors) for each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The figure is based on numbers that represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis.

ANOVA results:

- **Noise**  
  \( p\)-value=0.0499

- **Extremity\*Time**  
  \( p\)-value<0.0001

- **Noise\*Extremity\*Time**  
  \( p\)-value=0.0304
Figure 4
Liquidity: Temporary and Permanent Price Impact of Trades

This figure presents results on temporary and permanent price impact measures, tempimp and perimp, computed as averages over all transactions in a trading period. For a market order placed at time \( t \) denote the transaction price by \( P_t \), the midpoint between the best bid and offer prices in the limit order book (just before the trade) by \( M_t \), and the midpoint between the best bid and offer prices prevailing five trades after the market order for which we are computing the price impact by \( M_{t+5} \). The total price impact for a buy (sell) order is defined by \( P_t - M_t (M_t - P_t) \). The permanent price impact for a buy (sell) order is defined by \( M_{t+5} - M_t (M_t - M_{t+5}) \) and the temporary price impact is defined by \( P_t - M_{t+5} (M_{t+5} - P_t) \). Note that the total price impact is the sum of the permanent and temporary components. The figure provides information separately for each cell in the 2 (noise) x 2 (extremity) factorial design. The noise factor represents the presence of uninformed traders in the market and has two levels: Noise (in half of the cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and No Noise (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity (realized values that are at least $17$ from the expected value) and Low Extremity (realized values that are no more than $16$ from the expected value). We do not provide a breakdown by the tax factor since there were no statistically significant interactions or a main effect for this factor. Our statistical analysis relies on repeated-measures ANOVA. For analyses of market-level variables, such as tempimp and perimp, we judge statistical significance by computing the average of the dependent variable within each cell (defined by the appropriate factors) for each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The numbers in the table represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis.

\[
\begin{align*}
\text{Price Impact} \\
\text{Dollars} \\
\begin{array}{cc}
\text{Low Extremity} & \text{High Extremity} \\
\text{No Noise} & \text{Noise} \\
\text{No Noise} & \text{Noise}
\end{array}
\end{align*}
\]

\text{ANOVA results for tempimp:}
\begin{align*}
\text{Noise} & \quad p\text{-value}=0.0312 \\
\text{Extremity} & \quad p\text{-value}=0.0734
\end{align*}

\text{ANOVA results for perimp:}
\begin{align*}
\text{Noise} & \quad p\text{-value}=0.0046 \\
\text{Extremity} & \quad p\text{-value}<0.0001
\end{align*}
This figure presents the evolution of pricing errors over the trading period. To examine the behavior of pricing errors over the trading period, we divide the trading period into ten time intervals and compute the average pricing errors measure DEVP separately in each interval. DEVP is computed as the average over all transaction prices in an interval of the absolute value of the difference between the transaction price and the true value. The data reveal significant noise*extremity and extremity*time interactions, so we present the results separately for each cell in the 2 (noise) x 2 (extremity) x 10 (time intervals) factorial design. The noise factor represents the presence of uninformed traders in the market and has two levels: HN (in half of the cohorts there were four uninformed traders in the market in addition to the four informed and four liquidity traders) and LN (in half of the cohorts there were no uninformed traders in the market; only four informed and four liquidity traders). The extremity factor (how different the realized value of the security is from its unconditional mean) has two levels: High Extremity or HE (realized values that are at least $17 from the expected value) and Low Extremity or LE (realized values that are no more than $16 from the expected value). We graph the behavior of pricing errors over time for four cells: Low Noise (i.e., no uninformed traders) / Low Extremity (LNLE); Low Noise / High Extremity (LNHE); High Noise (i.e., uninformed traders are present) / Low Extremity (HNLE); High Noise / High Extremity (HNHE) The data do not indicate any tax interactions (or a main effect), so we do not segment the results according to tax regimes. Our statistical analysis relies on repeated-measures ANOVA. For analyses of market-level variables, such as DEVP, we judge statistical significance by computing the average of the dependent variable within each cell (defined by the appropriate factors) for each of the cohorts. A repeated-measures analysis effectively treats each cohort as providing a single independent observation of the dependent variable. The figure is based on numbers that represent the averages across the cohorts. Below the panel we provide all the main effects and interactions that were found significant in the ANOVA analysis.

**ANOVA results:**

- **Extremity**
  - p-value < 0.0001
- **Time**
  - p-value = 0.0197
- **Extremity*Time**
  - p-value < 0.0001
- **Noise*Extremity**
  - p-value = 0.0313