# Does Noise Trading Affect Securities Market Efficiency?

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**Abstract**

I investigate the impact of noise trading on securities market efficiency using data from short-horizon Arrow-Debreu securities traded on an online exchange. Using liquidity as a proxy for the amount of noise trading, I show that securities markets with persistently high noise trade exhibit significant pricing anomalies, such as overpricing low probability events and underpricing high probability events. By contrast, markets are remarkably efficient when there is low noise trade or when it is likely that securities' payoffs will be equal to their fundamental values. These findings are consistent with theoretical models in which rational agents face limits to arbitrage, but inconsistent with frictionless models in which increases in noise trading have no impact or a favorable impact on efficiency.

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Many theoretical models of securities prices incorporate agents who have hedging motives or irrational reasons to trade, which I call noise traders throughout the paper. Although the direct effect of adding such noise traders to a securities market is to reduce informational efficiency, standard models feature strong countervailing effects. Greater noise trade in a securities market motivates rational agents to trade more aggressively on their existing information and provides them with incentives to acquire better information. For these reasons, two of the most widely used models in finance, Grossman and Stiglitz (1980) and Kyle (1985), predict that an increase in noise trading will not harm informational efficiency. In fact, if one allows informed traders to acquire costly information, the Kyle (1985) model unambiguously predicts that an increase in noise trading leads to an improvement in informational efficiency.

There are, however, competing theoretical models in which rational agents do not fully offset noise traders' demands because of various limits to arbitrage. For example, in DeLong, Shleifer, Summers, and Waldmann (1990b), rational arbitrageurs sometimes reinforce demand shocks from noise traders because they anticipate mispricing will worsen in the short-run.[2] Models in which there are significant limits to arbitrage deliver the opposite prediction that greater noise trade harms informational efficiency.

I test these competing predictions from the theoretical literature in a real-world setting that allows particularly clean tests of whether noise trading affects market efficiency. Specifically, I use data from Arrow-Debreu securities based on one-day sports and financial events traded on an online exchange, TradeSports.com. Using three measures for the amount of noise trading, I show that securities markets with more noise

[2] Another notable example is DeLong, Shleifer, Summers, and Waldmann (1990a). In that model, risk-averse arbitrageurs attenuate their demands because they must liquidate their positions at uncertain prices set, in part, by noise traders.

trading exhibit significant pricing anomalies, whereas securities markets with less noise trading are remarkably efficient. The pattern in markets with significant noise trade is that low probability events are overpriced and high probability events are underpriced.

Although related work identifies similar pricing patterns in wagering markets (*e.g.*, Jullien and Selanie (2000), Wolfers and Zitzewitz (2004), and Zitzewitz (2006)) and financial markets (Rubinstein (1985), Brav and Heaton (1996), and Barberis and Huang (2005)), none of these studies draws a link between securities mispricing and market liquidity. The main contribution of this paper is to show that the Kahneman and Tversky (1979) pattern in securities mispricing is largely confined to liquid markets with high noise trade, and does not apply to illiquid markets. In fact, significant mispricing appears only in liquid securities experiencing persistently high noise trade in which mispricing could worsen in the short-run.

These results suggest that noise traders harm informational efficiency, particularly when rational informed agents have low incentives to offset noise traders' demands. The findings are consistent with theoretical models in which rational agents face limits to arbitrage, but inconsistent with frictionless models in which increases in noise trading have no impact or a favorable impact on efficiency. In addition, the specific pricing patterns suggest that Kahneman and Tversky's (1979) theory and evidence on individual behavior applies to noise traders.

This paper examines securities markets that are distinct from most real-world financial markets in several respects that make them desirable for testing efficiency. All the tests in this study use data on short-horizon binary outcome securities traded in a standard continuous double auction. Whereas long-run event studies require an accurate model for the price of systematic risk (Fama (1970 and 1991)), testing the efficiency of the short-horizon securities on the TradeSports exchange does not require these assumptions because the price of risk is typically negligible. Whereas it is impossible to observe securities' fundamentals in standard short-run and long-run event studies, one can directly observe the terminal payoffs of the securities on TradeSports at the end of their one-day horizons (Thaler and Ziemba (1988)).[3] The ability to measure absolute pricing efficiency is critical for testing market microstructure models, which almost exclusively use this efficiency criterion.

Tests of efficiency on TradeSports also possess some advantages relative to tests based on experimental and wagering market data. Whereas typical experimental markets involve student volunteers who trade tens of dollars at most, the TradeSports exchange attracts many real-world traders who routinely wager thousands of dollars. Whereas most wagering markets allow participants to place bets on only sporting events through parimutuel or fixed-odds mechanisms, the TradeSports exchange facilitates trades in sporting *and* financial events using standard continuous double auctions.[4] For these reasons, tests of efficiency using TradeSports data nicely complement the evidence from real-world and experimental financial markets and the evidence from wagering markets.

[3] Accordingly, this paper's tests of absolute pricing efficiency are not directly comparable to efficiency tests in traditional equity markets. For example, Chordia, Roll, and Subrahmanyam (2006) argue that liquidity increases market efficiency based on evidence from high-frequency return predictability tests. Because their efficiency tests do not examine any measures of stocks' fundamentals, their results are not necessarily inconsistent with this paper's main finding that liquidity decreases absolute pricing efficiency.

[4] Nearly all of the world's major stock, currency, commodity and derivatives exchanges facilitate trades through continuous double auctions. In both theory and practice, double auctions appear to be particularly robust mechanisms that promote rapid adjustment towards market equilibrium even in the presence of market frictions and trader irrationality. For theoretical models, see Gjerstad and Dickhaut (1998) and Satterthwaite and Williams (2002). For empirical evidence, see Gode and Sunder (1993), Friedman and Ostroy (1995), Cason and Friedman (1996), and Noussair *et al*. (1998).

This study relies on three indicators of the amount of noise trading that are motivated by microstructure models of securities market liquidity.[5] The first measure of noise trading is a low bid-ask spread because an increase in the fraction of noise traders lowers the equilibrium bid-ask spread in nearly all models (*e.g.*, Glosten and Milgrom (1985)). The second indicator of noise trading is based on how much prices move in the absence of trading, presumably as a result of information. Low information-based price movement implies that no significant public or private information has been revealed since the last trade, suggesting there is relatively more noise trading. Because these two measures of noise trading are strongly related to each other in theory and practice, I also consider a third measure based on their common component.[6] Using any of these three measures, I obtain the result that an increase in noise trading reduces informational efficiency—specifically, low probability events are overpriced and high probability events are underpriced.

To assess why markets with high noise trade appear less efficient, I examine whether markets with persistently high noise trade are different from those with high, but sporadic, noise trade. The main finding is that only markets with persistently high noise trade exhibit significant mispricing. One interpretation is that arbitrage can destabilize prices when arbitrageurs expect to be able to liquidate their positions in future transactions with noise traders (DeLong, Shleifer, Summers, and Waldmann (1990b)).

The layout of the paper is as follows. In Section I, I describe the structure of the securities data from the TradeSports exchange and the measures of noise trading used

[5] Microstructure models often use the terms liquidity traders and noise traders interchangeably.
[6] I use the standardized average of the spread and information-based price movement measures of noise trade to measure their common component. Alternative linear combinations of the two measures produce similar results.

throughout the paper. In Section II, I perform the basic efficiency tests for securities markets with relatively more noise trading. In Section III, I examine how the magnitude of these results depends on the incentives for arbitrageurs to offset noise traders' demands. In Section IV, I conclude and suggest directions for further research on the impact of noise traders.

## I. Securities Data and Measures of Noise Trade

I construct an automatic data retrieval program to collect comprehensive statistics at 30-minute intervals on each security traded on the TradeSports exchange.[7] The program runs almost continuously from March 17, 2003 to August 17, 2006. [8] All empirical tests in this paper include only data from the one-day sports and financial securities recorded by the program. I focus on these securities to limit the number of factors needed as controls in the statistical analysis. The vast majority of TradeSports' securities are based on one-day sports or financial events, such whether the Yankees will win a particular baseball game or whether the Dow Jones Index will close 50 or more points above the previous day's close.[9] Roughly 70% of TradeSports' securities are based

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[7] I am grateful to TradeSports Exchange Limited for granting me permission to run this program. The program's 30-minute interval is approximate because it records securities sequentially, implying that the exact time interval depends on whether new securities have been added or subtracted and precise download speeds. In practice, these factors rarely affect the time interval by more than one or two minutes.

[8] The program stops running only for random author-specific events, such as software installations, operating system updates, power failures, changing offices, and similar reasons—and technical TradeSports issues, such as daily server maintenance and occasional changes in the web site's HTML code.

[9] For sports events, I consider only securities with an official TradeSports categorization that includes either the text "game," "bout," or "match"; for financial events, I consider only securities that do not include "weekly," "monthly," or "yearly," and were not recorded more than one week before the expiration day. Over 96% and 99.6% of qualifying financial securities expire on the day of or the day after listing, respectively. Even though virtually all of the uncertainty for qualifying sports and financial events is resolved on the day in which the security expires, some securities are listed and traded on the exchange before the expiration day. I keep all observations within one week of the expiration day.

on sports events, 25% are based on financial events and fewer than 5% are based on events in all other categories combined—*e.g.*, political, entertainment, legal, weather, and miscellaneous.

The TradeSports exchange facilitates the trading of binary outcome securities by its members, and does not conduct transactions for its own account.[10] Securities owners receive $10 if a pre-specified, verifiable event occurs and $0 otherwise—*e.g.*, the owner of the Dow Jones security mentioned above receives $10 if and only if the index goes up by 50 points or more. For ease of interpretation, the exchange divides its security prices into 100 points, worth $0.10 per point. The minimum price increment, or tick size, ranges between one point for thinly traded securities and 0.1 point for heavily traded securities.

TradeSports levies a commission equal to 0.4% of the maximum securities price ($10) on a per security basis whenever a security is bought or sold.[11] At the time of security expiration, all outstanding securities positions must be liquidated and incur commissions.[12] Note that the $0.08 round-trip transaction fee is smaller than the value of one point ($0.10) for most securities. This implies arbitrageurs have an incentive to push prices back towards fundamental values if they stray by even one point.

Because most microstructure models assume there is an active market maker, I exclude securities on the exchange where market makers are not likely to be active participants. Thus, I exclude the roughly 25% of observations with cumulative trading volume below 10 securities ($100), market depth below 100 securities ($1,000), or bid-

[10] TradeSports limits the risk that the counterparty in a security transaction will default by imposing stringent margin requirements for each sale or purchase of a security by one of its members. In most cases, members must retain sufficient funds in their TradeSports account to guard against the maximum possible loss on a transaction. TradeSports also settles and clears all transactions conducted on its exchange.
[11] The exchange has recently eliminated commissions for non-marketable limit orders.
[12] Expiration is the time at which the payoff event is verifiable and the owner receives payment.

ask spreads exceeding 5% ($0.50).[13] I compute market depth as the sum of all outstanding buy and sell limit orders within five points of the security's bid-ask midpoint. These restrictions also exclude economically insignificant observations and price data of such poor quality that testing market efficiency would not be meaningful. Indeed, if no agent actively monitors the limit order book, it is difficult to argue that a market exists.

I use two measures for the amount of noise trading based on theoretical microstructure models, and a third measure which is a composite of the first two. To maximize the power of the statistical tests that follow, I partition the qualifying observations on securities into two equal-sized halves based on the presumed amount of noise trading according to each of the three measures.[14]

The first indicator for the amount of noise trading is a low bid-ask spread. Following convention, I define the spread as the difference between the inside (lowest) ask and (highest) bid quotations. I consider all securities markets with spreads below the median, usually around $0.20, to have high noise trade and all other securities to have low noise trade.[15] To avoid any look-ahead bias in the cutoff value, I use the median spread from the distribution of all observations on TradeSports securities over the prior six calendar months.

The second indicator of noise trading is based on the absolute deviation between the bid-ask midpoint and the previous transaction price, which I call information-based price movement. I infer that securities markets with large information-based price

[13] From anecdotal evidence, market makers' quoted spreads rarely exceed five points and quoted depths are rarely smaller than 100 securities.
[14] Other partitions, such as quartiles based on the presumed amount of noise trade, produce similar results.
[15] Using the median spread from the previous six months as the cutoff does not divide securities into two groups of identical size because of lumpiness in the distribution of spreads and changes in the spread distribution over time. In the first six months of data, I use the median of all spreads in the sample to date. Using *ad hoc* spread cutoffs of $0.10, $0.20 and $0.30 produces qualitatively similar results.

movements have high informed trading—*i.e.*, low noise trading. For example, suppose that the last trade price is 66 points and the current bid and ask quotations are 67 and 69 points, implying the midpoint is 68 points. The two-point price movement after the most recent trade implies that traders adjusted their quotations as a result of public information that arrived after the last trade. One way to think of this information-based price movement is in terms of the price impact of trading, or absolute value of returns per dollar traded (*e.g.*, Amihud (2002)). If prices move two points when there is no trading, then the price impact of trading is infinite. In models such as Glosten and Milgrom (1985), the price impact of trading is a measure of informed trading—*e.g.*, an infinite price impact implies there is no noise trading. Generalizing this logic, information-based price movement should be inversely related to noise trading.

One can also interpret information-based price movement as a measure of public information. When there is considerable public information, knowledgeable experts are likely to have significant private information because experts can extract more precise signals from common public information. For example, when the Boston Celtics' star player fouls out of a basketball game, a Celtics expert has an especially accurate estimate of the implication of this event for the team's likelihood of victory. As a result, there is more informed trading and relatively less noise trading when information-based price movement is high. I categorize all trades with below-median information-based price movement, usually around $0.10, as "low-info" securities and all others as "high-info" securities. I use the median information-based price movement from all TradeSports securities over the past six months as the cutoff value.

One would hope that two different measures designed to capture the same noise trading phenomenon would exhibit some degree of similarity. Indeed, I find that the correlation between the bid-ask spread and (the logarithm of) information-based price movement is over 60%, which is strongly statistically significant at any level.[16] This is comforting in that the two measures probably describe some common component of market activity.

For this reason, I compute a third measure of noise trade as the standardized average of the bid-ask spread and the logarithm of information-based price movement.[17] To standardize each variable, I subtract its mean over the past six months and divide by its standard deviation. I label the securities with below-median values of this third measure of noise trade as "low-noise" securities and all others as "high-noise" securities, where I use the median from the prior six months of data as the cutoff value.

## II. Tests of Market Efficiency

Now I analyze the absolute pricing efficiency of securities on the TradeSports exchange. I conduct these tests separately for the high-noise securities, the low-noise securities, and all securities. I also analyze the efficiency of sports and financial markets separately based on the results in Tetlock (2004), which reports evidence that pricing in

[16] I compute the logarithm of (0.1 + information-based price movement) to reduce the substantial skewness in this measure before computing the correlation between information-based price movement and spreads. Adding 0.1 allows me to compute the log for information-based price movements of zero and makes the minimum price movement equal to the minimum spread of 0.1 point. I do not calculate logarithms of the spread variable because it is already censored at five points and exhibits very little skewness. The correlation between raw spreads and raw information-based price movements is greater than 50%.
[17] This is equivalent to using the first factor in a principal components analysis of the two variables.

these markets differs significantly. The key results in this study apply equally to sports securities and financial securities, regardless of their exposure to market risk.[18]

I employ a straightforward regression methodology to test the null hypothesis that a securities market is efficient. A single observation consists of a security's current price and its returns until expiration. I measure all current prices using the midpoints of the inside bid and ask quotations to avoid the problem of bid-ask bounce that could affect transaction prices.[19] I calculate a security's percentage returns to expiration by subtracting its current price from its expiration value, which is either 0 or 100 points, then dividing by 100 points.[20] The null hypothesis is that securities' expected returns to expiration are zero, regardless of the current securities price. The alternative hypothesis is that Kahneman and Tversky's (1979) theory of probability perception describes the pattern of expected returns across securities with different current prices.

The S-shaped form of the probability weighting function hypothesized in Kahneman and Tversky (1979) and formalized in Prelec (1998) informs my choice of pricing categories and statistical tests.[21] Prelec (1998) builds a theory of probability misperception based on axiomatic foundations. He predicts that agents overestimate the likelihood of events with objective probabilities less than $1/e$ (0.3679 or 36.79%) and underestimate the likelihood of events with objective probabilities greater than $1/e$. There is also an ample body of empirical evidence that is consistent with a probability

[18] In unreported tests, I allow for the possibility that financial securities with positive exposure to market risks have different expected returns from those with negative risk. I find a positive, but insignificant, risk premium of less than 1% for the typical financial security with positive exposure to the market. This is not surprising because three years of data is usually insufficient for estimating market risk premiums.
[19] All results are robust to using the most recent transaction price instead.
[20] I exclude the very small fraction of TradeSports contracts that do not expire at 0 or 100 points. I divide by 100 points to represent the combined amount of capital that buyers and sellers invest in the security.
[21] The S-shape refers to a graph of subjective versus objective probabilities (Kahneman and Tversky (1979)).

weighting function having a fixed point in the neighborhood of 1/*e* (Tversky and Kahneman (1992), Camerer and Ho (1994), and Wu and Gonzalez (1996)).

Based on this evidence, I construct dummy variables (Price1 through Price5) for five equally-spaced pricing intervals: (0,20), [20,40), [40,60), [60,80), and [80,100) points. I then measure the returns until expiration for securities in each pricing category. I test the null hypothesis that all returns to expiration are equal to zero against the alternative that securities in the first two categories (Price1 and Price2), based on small probability events ($p < 40\%$), are overpriced and securities in the last three categories (Price3, Price4 and Price5), based on large probability events ($p > 40\%$), are underpriced.

I report the results from three Wald (1943) tests based on this simple idea. The first Wald test measures whether small probability events are overpriced on average:[22]

$$\text{(Price1 + Price2) / 2 = 0} \tag{1}$$

The second Wald test assesses whether large probability events are underpriced:

$$\text{(Price3 + Price4 + Price5) / 3 = 0} \tag{2}$$

The third Wald test measures whether large probability events are more underpriced than small probability events—*i.e.*, whether the mispricing function is S-shaped:

$$\text{(Price3 + Price4 + Price5) / 3 – (Price1 + Price2) / 2 = 0} \tag{3}$$

Of the three, this is the most powerful test of the null hypothesis against the Kahneman and Tversky (1979) alternative because it accounts for other factors that could influence the level of mispricing of both small and large probability events.[23]

[22] Despite the specific nature of over- and underpricing predicted by Kahneman and Tversky (1979), I use a two-tailed test to remain conservative.

[23] Note that the choice of how to partition the pricing categories has little affect on the Wald tests because, regardless of the partitioning, these tests assess whether the returns to expiration of securities priced below 40 points differ from the returns of securities priced above 40 points.

I use standard ordinary least squares to estimate the coefficients of the five pricing categories. For all regression coefficients, I compute robust standard errors to account for the repeated sampling of the same security over multiple time periods and the sampling of different securities based on related events. I employ the clustering methodology developed by Froot (1989) to allow for correlations in the error terms of all securities expiring on the same calendar day, which simultaneously corrects for repeated sampling of the same security and sampling of related events. This clustering procedure exploits the fact that all event uncertainty is resolved on the day of expiration (see footnote 9).

To illustrate the efficiency tests and give an overview of the data, I first examine the returns to expiration for all sports securities, all financial securities and both groups together. Table I displays the regression coefficient estimates for Price1 through Price5 along with the three Wald tests described above. The main result is that neither sports nor financial securities exhibit substantial mispricing, which is consistent with Wolfers and Zitzewitz (2004) and Tetlock (2004).

[Insert Table I around here.]

The qualitative patterns in the pricing of both sets of securities and in their aggregate suggest, however, that the probability weighting function could play a role in any mispricing that does exist. For example, the securities based on small probability sports events appear to be overpriced by 1.33 points (p-value = 0.097) and financial securities based on large probability events are underpriced by 2.00 points (p-value = 0.062). The more powerful test for the S-shaped pattern rejects the null hypothesis that returns do not differ across pricing categories at the 5% level for both sports and financial securities. Interestingly, the magnitude of mispricing decreases from an average of over two points across the sports and financial groups to just 1.38 points in the aggregate group, which is significantly different from zero at only the 10% level. This reduction occurs because of differences in the pricing patterns of sports and financial securities and the changing relative composition of sports and financial securities within pricing categories. This disparity between the average of the individual estimates and the aggregate estimate also illustrates why it is important to estimate the effects on sports and financial securities separately.

Having established that both sports and financial securities both show a limited degree of inefficiency, I now turn to the key test of whether the S-shaped Kahneman and Tversky (1979) pattern is more pronounced in securities with more noise trading. Table II reports the results from nine regressions that attempt to address this question using the composite measure of noise trading. The table includes separate regression results for sports, financial and all securities sorted by the amount of noise trade in each security type. The tests for differences in the coefficients (Columns Three, Six, and Nine) come from joint regressions in which I estimate coefficients on Price1 through Price5 for both high- and low-noise securities simultaneously by adding five interaction terms—between noise trade and Price1 through Price5.

[Insert Table II around here.]

For both sports and financial securities, the S-shaped probability weighting function pattern is strongly statistically and economically significant in only the securities with high noise trade. For example, the S-shaped pattern is non-existent in the low-noise sports securities (-0.08 points), but is quite pronounced in the high-noise sports securities (3.88 points, p-value = 0.003). Similarly, the S-shaped pattern is insignificant and small in the low-noise financial securities (1.85 points), but strongly significant and large in the high-noise financial securities (6.58 points, p-value < 0.001). Moreover, the two tests for whether the S-shaped patterns are more pronounced in the high-noise securities than in the low-noise securities reject the null hypothesis at the 1% level. Again, this rejection is slightly weaker for the aggregate of sports and financial securities, but still significant at the 5% level.

Note that the signs of 19 of the 20 individual coefficients on the high-noise securities and interaction terms in the sports and financial security regressions agree with the predictions of the S-shaped probability weighting function. This precise pattern in mispricing is highly unlikely to occur by chance (p-value < 0.001). Indeed, the qualitative pattern in the coefficients explains why, even though only a few of the individual coefficients on the pricing category dummy variables are statistically significant, the Wald tests for the S-shape easily reject the null hypothesis of zero returns.

The magnitude of the S-shaped pattern is surprisingly similar for the sports and financial securities (3.97 points vs. 4.73 points). Using the same noise trade cutoff value for both types of securities, however, I find that a much greater fraction of the sports securities fall into the high noise trade classification (57.9%) relative to the financial securities (10.8%).[24] One interpretation is that noise trading is more widespread in sports securities, but that the effect of noise trading on prices is similar for different security types.

Figure 1 graphically represents the difference in returns to expiration for the low-noise and high-noise sports and financial securities in each of the five pricing categories. The vertical axis shows the returns to expiration for each security grouping

[24] This disparity is one disadvantage of using the same cutoff value for both security types.

while the horizontal axis shows the pricing categories. The visual impression from the figure confirms the statistical results in Table II: the difference in returns to expiration for each security type shows a distinct S-shaped pattern. In high-noise securities, the overpricing of low probability events is much more severe, especially in sports securities, and the underpricing of high probability events is far more severe, especially in financial securities.

[Insert Figure 1 around here.]

If one accepts market liquidity as an adequate proxy for noise trade, these results suggest that noise traders cause significant harm to pricing efficiency in exactly the manner predicted by the classic S-shaped probability weighting function. Although I measure noise trade using securities market liquidity, the findings in Table II are distinct from the well-known empirical relationships between liquidity risk and expected returns in traditional financial markets (Pastor and Stambaugh (2003)). On the TradeSports exchange, there is little room for interpreting the expected returns on liquid securities as compensation for risk because the sports securities exhibit the same pattern as the financial securities even though they are not susceptible to systematic risks.

I now explore the ability of the two individual liquidity measures, spreads and information-based price movement, to capture the effect of noise trading. Table III reports the returns to expiration of various securities sorted by whether their bid-ask spreads fall below the median spread on the TradeSports exchange during the previous six-month period. As in Table II, each column in Table III represents a different linear regression with dummy variables for each of the five pricing categories. Columns One and Two show that the sports securities with relatively low spreads have returns to expiration that exhibit a strong S-shaped pattern across pricing categories, whereas the high-spread securities show no such pattern. Columns Five and Six display the analogous result for financial securities. The magnitude of the S-shaped pattern is roughly four points greater for the sports and financial securities that have relatively low spreads, which is similar to the magnitude for sorts based on the composite measure of noise trade.

[Insert Table III around here.]

Table IV reports the returns to expiration for each of the five pricing categories for securities sorted by whether their information-based price movement falls below the median information-based price movement on the exchange during the previous six-month period. Columns One and Two establish that the low-info sports securities have returns to expiration that exhibit a strong S-shaped pattern across pricing categories, whereas the high-info securities show no such pattern. Columns Five and Six reveal that the same result applies to financial securities. Again, the magnitude of the S-shaped pattern is roughly four points greater for the sports and financial securities that have relatively low information-based price movements.

[Insert Table IV around here.]

Figure 2 visually summarizes the regression results in Tables III and IV by showing the difference between the pricing category coefficients from Columns Three and Six in the two tables. The differences between the pricing category coefficients have the sign predicted by the S-shaped pattern in 19 out of 20 cases, which is virtually impossible to occur by chance ($p$-value $< 0.001$). This visual and intuitive evidence is consistent with the numerical impression from the tables.

[Insert Figure 2 around here.]

Finally, note that Tables III and IV show that far more sports securities qualify for the high noise trade classification (more than 50%) than financial securities (fewer than 20%), regardless of which liquidity measure one uses. The reader should bear this fact in mind when interpreting the mispricing results throughout this paper, especially those in the next section that apply only to the high-noise securities.

## III. Mispricing in Securities with High Noise Trade

In this section, I focus on the securities on TradeSports that qualify as high noise trade securities to examine whether other factors influence the degree of mispricing. Motivated by theoretical models, I employ one key variable and four subsidiary variables to measure the *relative* influence of noise traders versus rational informed traders. These five measures could play a role in mispricing because they affect informed traders' ability or willingness to offset the demands of noise traders.

The first and foremost indicator of whether noise traders exert an influence on equilibrium securities prices is the persistence of noise trade. Theoretical models such as DeLong, Shleifer, Summers, and Waldmann (1990a and 1990b) suggest that informed traders are more reluctant to offset the demands of noise traders, and may even reinforce their demands, when there is a risk that mispricing will worsen in the short-run. Increases in mispricing can only occur in securities with persistent noise trade because liquidity is necessary for arbitrageurs to liquidate their positions at prices that may differ from securities' fundamental values.[25]

For example, consider a Celtics-Lakers basketball game security with a 100% objective likelihood of expiring at 100 points, a current bid price of 89 points, and a current ask price of 91 points—*i.e.*, the security is currently underpriced by 10 points. Suppose that this security is persistently liquid and, with some significant probability, will trade at bid and ask prices of 84 and 86 points in 30 minutes. Informed traders may be reluctant to purchase this security at the current ask price of 91 points for two related reasons. First, risk-averse informed traders may fear the risk that mispricing could worsen in the short-run. Second, informed traders with insights into noise traders' future beliefs may be able to profit from selling the security now and buying it back in 30 minutes. By contrast, if informed traders expect that noise trader demand will attenuate in the future, they will purchase the security now and sell it after its price converges to fundamentals.[26]

I test models of limited arbitrage by examining whether mispricing is greater in securities with persistent liquidity. I consider securities that qualify for the high noise trade classification in five consecutive data recording periods (over two hours) to exhibit "persistent noise trade," and all others to exhibit "sporadic noise trade."[27] Because the

[25] Persistent noise trade could also serve as a proxy for capital constraints faced by arbitrageurs who have exhausted their capital. In unreported tests, I find that more specific measures of capital constraints produce only weak results. This could occur because the measures are poor or because the dollar volumes on the exchange are too low to observe constrained arbitrageurs.
[26] If noise trader demand attenuates to the point at which no trading takes place, then informed traders must wait until expiration to liquidate their positions. This would lead to some fundamental risk if informed traders did not have perfect information, which they do in this simple example.
[27] The results are similar for cutoff values of two and three times in a row. Using cutoff values higher than five eliminates many events from the sample because this would require nearly three hours of consecutive observations and many events do not last this long. It is likely that securities based on events near expiration will yield payoffs equal to their fundamental values.

noise trade classification shows strong positive serial correlation, over 30% of high-noise securities meet the criterion for persistent noise trade.[28]

Because the other four proxies for the influence of noise traders are less firmly linked to theory, I report the results for these measures primarily as a robustness check. The second proxy is the existence of an order imbalance, which is based on Grossman and Miller's (1988) definition of a "liquidity event." In their model, noise traders submit unequal quantities of buy and sell orders in a given time period, which empirically manifests itself as an order imbalance. I define an imbalance as the difference between outstanding buy and sell limit orders that are within five points, or $0.50, of the bid-ask midpoint.[29] The intuition is that noise traders experiencing a liquidity event will submit either limit or market orders that lead to deviations in the sums of buy and sell orders in the limit order book. To compute the scaled order imbalance for each security, I divide the buy-sell imbalance by the market depth. I label all securities with above-median scaled order imbalances, or 3.72%, as "high imbalance" and all others as "low imbalance."[30] If noise traders have a greater effect on prices in markets with liquidity events, then the S-shaped pattern in high-noise securities may be stronger for high-imbalance securities.

The third proxy for the influence of noise traders is a lack of recent changes in securities prices during the previous 30-minute data recording period.[31] In standard market microstructure models, changes in prices indicate that new information is arriving

[28] Less than 0.2% of the persistent noise trade securities are financial securities because noise trade is not persistent or common in financial securities. I confirm, however, that the qualitative results are similar for financial securities that exhibit high noise trade in two consecutive data recording periods.
[29] Recall that five points is the maximum bid-ask spread for all securities in this sample.
[30] The qualitative results are similar if I use scaled imbalance cutoffs of 1% or 5% instead.
[31] This measure is distinct from the information-based price movement measure because it also captures price movements that result from trades and covers a longer time period.

at the market via trades from rational informed traders. It is reasonable to suppose that the arrival of new information increases informed trading—*e.g.*, because there are greater profits from informed trading when there is more information. To quantify this effect, I label all securities with above-median absolute changes in prices as “some news” securities, and all others as “no news” securities. The above reasoning suggests that the S-shaped pattern in mispricing may be more pronounced for “no news” securities.

As a fourth measure of the influence of noise traders, I examine trading volume, which is typically the outcome of a transaction between a noise trader and an informed trader.[32] In liquid markets where noise traders outnumber informed traders, informed traders may require some compensation to hold the inventory positions required to offset noise trade. This compensation presumably increases with the size of the transaction between the two parties because larger inventory positions require greater margin and entail greater risk. Thus, the S-shaped pattern in mispricing may be more pronounced in “high volume” liquid markets, where volume exceeds the median value for the TradeSports exchange.

As the fifth proxy for the influence of noise traders, I consider the length of time until a security reaches expiration. Models such as Shleifer and Vishny (1990) predict that mispricing will be greater for securities that take longer to reach their fundamental values. The reason on the TradeSports exchange is that mispricing may worsen in the short-run, which reduces the demand from risk-averse informed traders. Although all of the securities in this sample are based on one-day events where uncertainty is resolved on the expiration day, there is a small amount of variation in when trades in these securities

[32] For example, in the absence of noise traders, Milgrom and Stokey’s (1982) model predicts that there would be no trading of securities such as those listed on the TradeSports exchange.

occur. Accordingly, I test to see whether the S-shaped mispricing pattern is greater for securities traded before their expiration day—by at most one week—as compared to securities traded on the day of expiration.

Table V reports the results from the tests of whether persistent noise trade and order imbalances affect the degree of mispricing in high-noise securities. The most important result is that high-noise securities with persistent noise trade show significantly greater mispricing. The test for whether the S-shaped pattern is equally pronounced in high-noise securities with persistent noise trade rejects the null hypothesis at the 1% level. This result is reassuring because the persistent noise trade measure closely corresponds to the classic theoretical risk that mispricing worsens in the short-run. It appears that arbitrageurs do not offset, and may even reinforce, noise traders' probability misperceptions in securities that exhibit persistent noise trade. However, arbitrage is quite effective in the high noise trade securities that experience sporadic noise trade, where mispricing is less than one-fifth as large (1.62 points vs. 9.05 points).

[Insert Table V around here.]

Figure 3 compares the returns to expiration of securities with low noise trade, those with high but sporadic noise trade, and those with persistently high noise trade. The immediate impression from the figure is that the dark gray bars representing the mispricing of securities with persistently high noise trade are very large relative to the mispricing bars for other securities. Comparing the white and the light gray mispricing bars, one sees that the S-shaped pattern is only slightly larger in securities with high but sporadic noise trade relative to securities with low noise trade (1.62 points vs. 0.52 points). There is virtually no mispricing in securities without persistent noise trade even when there is currently a large amount of noise trade. In other words, arbitrageurs effectively offset noise traders' demands when they do not anticipate future noise trade demand to exacerbate the current mispricing—*i.e.*, they expect the security to yield a payoff equal to its fundamental value at expiration.

[Insert Figure 3 around here.]

For the other four measures of noise trader influence, the results qualitatively conform to the theoretical arguments above. Panel A in Table VI reports the returns to expiration for high-noise securities sorted by whether there is a liquidity event (high order imbalance) and whether there is some news (a recent change in prices). Panel B in Table VI displays the returns to expiration for high-noise securities according to their cumulative trading volume and whether they expire on the current calendar day.

[Insert Table VI around here.]

Although the magnitudes of the S-shaped patterns in securities with high noise trader influence are more than twice the magnitudes in the low influence securities, none of the differences in magnitude is strongly statistically significant—*i.e.*, p-values range between 0.0825 and 0.1590. Nevertheless, one can say with great certitude that high-noise securities that experience liquidity events, have little news, attract high trading volume, or are not expiring on that day exhibit a strong S-shaped pattern (p-values < 0.01).[33] By contrast, the magnitude and statistical significance of the S-shaped pattern is considerably weaker in the securities where one would expect informed traders to exert a greater influence on equilibrium prices.

[33] The difference in short- and long-horizon securities could be driven by football games traded prior to game day, which show a strong S-shaped pattern. Using the TradeSports data alone, it is difficult to know whether this pattern is attributable to something football-specific or a more general pattern in long-horizon securities.

Figure 4 depicts the evidence in Table VI graphically. The most noteworthy aspect of the figure is that 16 of the 20 differences in pricing category coefficients have the sign predicted by theoretical models of noise trader influence. This pattern is highly unlikely to occur by chance (p-value = 0.0059). The figure also shows that certain proxies for the influence of noise traders, such as the "no news" proxy, have a greater impact on the overpricing of low probability events, whereas other proxies, such as the "high imbalance" proxy, have a greater effect on the underpricing of high probability events.[34] Qualitatively, virtually all of the proxies for noise trader influence exacerbate the S-shaped pattern of mispricing.

[Insert Figure 4 around here.]

As a final check on the magnitude and relevance of the mispricing in securities with high noise trade, I explore the profitability of a simple trading strategy based on the initial pattern of mispricing identified in Table II.[35] A natural trading strategy would be to sell all of the overpriced high-noise securities in pricing categories 1 and 2, and buy all of the underpriced high-noise securities in pricing categories 3, 4, and 5. I augment this simple rule to reflect the stylized fact that the overpricing of low probability events is more severe in sports securities. I also disregard the financial securities because these are few in number and could be susceptible to systematic risk. Thus, I analyze the trading strategy that sells high-noise sports securities in pricing categories 1 and 2.[36]

To make this trading strategy implementable, I assume that a trader submits a market order to TradeSports as soon as the automated data retrieval program records a

[34] Unreported tests reveal that the "no news" proxy captures noise trader influence better for sports securities, whereas the order imbalance proxy works best in financial securities.
[35] Obviously, one can improve upon this trading strategy using the information in Tables III through VI.
[36] A number of closely related trading strategies yield profits that are comparable in magnitude.

price on the exchange. Thus, all buy orders execute at the lowest asking price and all sell orders execute at the highest bid price at the time of retrieval. Unfortunately, this means that the trader must bear a substantial liquidity cost, which he or she could possibly avoid by using a limit order.[37] In addition, I assume that the trader must incur the maximum round-trip commission on TradeSports, which is 0.8% per round-trip. This set of assumptions leads to a conservative estimate of realizable trading returns.

[Insert Table VII around here.]

Despite the substantial liquidity and commission costs of implementing the strategy, Table VII reports that selling the sports securities in pricing categories 1 and 2 yields realizable expected returns of 2.14% and 0.89% over the time span of a day or so.[38] Table VII also shows that buying the financial securities in pricing categories 3, 4, and 5 produces expected returns of 2.98%, 5.60% and -0.80%. Figure 5 visually represents this evidence on returns to expiration for buyers and sellers of sports and financial securities. The expected returns in Table VII and Figure 5 are not weighted by the amount of capital that could be invested in each security and do not account for the cost of obtaining this capital.

[Insert Figure 5 around here.]

I make three additional assumptions to address these issues and obtain a conservative estimate of the total dollar profits from the strategy that sells high-noise sports securities in pricing categories 1 and 2. First, I assume that a retail investor could establish a line of credit allowing her to access capital at an annualized interest rate of

[37] Strategies using complex limit order rules may be profitable, but this is extremely difficult to evaluate because of the adverse selection problem associated with the execution of standing limit orders.
[38] The vast majority of the securities expire within the same day.

10%, or 0.027% per day.[39] Second, to simplify strategy implementation, I consider a strategy based on short-selling only the sports securities in pricing categories 1 and 2 that expire on the same calendar day in which the data retrieval program records their prices.[40] Third, I assume that the investor submits a market sell order for the quantity of securities exactly equal to the size of the current inside bid quote.

I find that this trading strategy earns an average of only $231 per day over the course of the 679 days in which it is implementable. Restated in more familiar terms, the strategy yields a total of $157,000 during the 1,059-day data sample, or $54,000 per year. Based on this analysis, there appears to be sufficient competition on the TradeSports exchange to ensure that realizable trading profits do not become too large. A wage of $54,000 per year is a reasonable ballpark estimate of the equilibrium compensation for actively monitoring the securities on the exchange.

## IV. Conclusions

Using data from real-world financial markets to uncover the complex relationships between noise trading and market efficiency is a daunting task. Rather than confront this task directly, I conduct tests of absolute pricing efficiency using data on simple short-horizon securities with negligible exposure to systematic risk. The hope is that identifying empirical regularities in these simple securities can inform future theoretical and empirical studies of more complex environments.

[39] I assume the investor pays a full day's worth of interest for funds used less than 24 hours.
[40] To be conservative, I assume traders must post margin equal to the maximum possible loss in order to sell a security—*e.g.*, a trader must post $8 to sell a security priced at $2 because it could expire at $10.

In this simple setting, tests of market efficiency consistently reject theoretical models in which noise traders either do not affect or enhance informational efficiency. Securities markets with more noise traders show significant pricing anomalies, such as overpricing low probability events and underpricing high probability events. These pricing patterns correspond closely to the predictions of Kahneman and Tversky's (1979) probability weighting function, suggesting that their theory may apply to noise traders. Conversely, the securities markets where few noise traders are present appear to be remarkably efficient.

Even more remarkable, only the highly liquid markets with persistent noise trade exhibit the S-shaped pattern of mispricing. Prices in securities markets in which noise trade is high at the moment, but could dissipate in the future, are reasonably accurate forecasts of empirically observed event frequencies. These findings are consistent with the model of DeLong, Shleifer, Summers, and Waldmann (1990b) in which rational arbitrageurs do not stabilize prices because they anticipate future noise trader demand. As a result of this limited arbitrage, small unexploited arbitrage opportunities remain in equilibrium. However, competition among arbitrageurs appears sufficient to prevent the equilibrium trading profits from becoming excessive.

Although these results are unlikely to generalize without modification to real-world financial markets with long-horizon securities, they do suggest three interesting directions for future research. First, liquidity may appear to be a priced risk factor because it captures some systematic element of mispricing. Second, future theoretical models could distinguish between persistent liquidity and sporadic liquidity. Third, because there appear to be significant limits to arbitrage on an online exchange with few capital constraints and securities that expire within a single day, the limits to arbitrage on real-world exchanges may be more severe than previously thought.

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**Table I: Returns to Expiration for Different Types of Securities**

This table reports the results from three ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5. The three regressions include observations of the returns and prices of securities based on one-day sports, financial and all events recorded at 30-minute intervals in which there is active trading (see text for more details). I compute returns to expiration as the payoff at expiration, 0 or 100 points, minus the bid-ask midpoint divided by 100 points. I construct dummy variables (Price1 through Price5) for five equally-spaced pricing intervals: (0,20), [20,40), [40,60), [60,80), and [80,100) points. The small probabilities row displays the magnitude and significance of the average coefficient on Price1 and Price2. The large probabilities row displays the magnitude and significance of the average coefficient on Price3, Price4 and Price5. The large minus small row reports the magnitude and significance of the difference in these two averages. I compute clustered standard errors to account for correlations within and across securities that expire on the same calendar day (Froot (1989)).

| | Sports | Financial | All |
|---|---|---|---|
| 0 < Price < 20 | -2.19*** | -0.49 | -0.79 |
| | (0.72) | (0.65) | (0.55) |
| 20 ≤ Price < 40 | -0.48 | -0.16 | -0.32 |
| | (1.39) | (1.21) | (0.93) |
| 40 ≤ Price < 60 | -0.10 | 1.63 | 0.01 |
| | (0.52) | (1.44) | (0.50) |
| 60 ≤ Price < 80 | 1.08 | 2.97* | 1.35* |
| | (0.87) | (1.53) | (0.77) |
| 80 ≤ Price < 100 | 0.93 | 1.40 | 1.11* |
| | (0.91) | (0.89) | (0.65) |
| Small Probabilities | -1.33* | -0.32 | -0.56 |
| | (0.80) | (0.84) | (0.63) |
| Large Probabilities | 0.64 | 2.00* | 0.82* |
| | (0.50) | (1.07) | (0.43) |
| Large – Small | 1.97** | 2.32** | 1.38* |
| | (0.92) | (1.11) | (0.74) |
| R-squared | 0.0002 | 0.0013 | 0.0002 |
| Expiration Days | 1049 | 732 | 1059 |
| Observations | 168604 | 39854 | 208458 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

**Table II: Returns to Expiration for Different Securities Sorted by Amount of Noise Trade**

This table reports the results from nine (3x3) ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5 (see text or Table I for details). The nine regressions include three sets of regressions for securities based on one-day sports, financial and all events. Each set includes regressions for low noise trade, high noise trade, and both groups of securities (see text for construction).

| | Sports | | | Financial | | | All | | |
|---|---|---|---|---|---|---|---|---|---|
| | Low Noise | High Noise | High – Low | Low Noise | High Noise | High – Low | Low Noise | High Noise | High – Low |
| 0 < Price < 20 | -1.09 | -3.53*** | -2.44* | -0.42 | -0.52 | -0.11 | -0.49 | -1.94** | -1.45* |
| | (0.92) | (1.03) | (1.34) | (0.68) | (1.05) | (0.99) | (0.62) | (0.78) | (0.86) |
| 20 ≤ Price < 40 | 1.60 | -2.33 | -3.93* | 0.14 | -3.69* | -3.83* | 0.64 | -2.48 | -3.12* |
| | (1.36) | (2.03) | (2.16) | (1.22) | (2.22) | (1.99) | (0.91) | (1.81) | (1.84) |
| 40 ≤ Price < 60 | -0.62 | 0.28 | 0.90 | 1.27 | 4.95* | 3.68 | -0.38 | 0.33 | 0.71 |
| | (0.53) | (0.67) | (0.66) | (1.44) | (2.79) | (2.50) | (0.50) | (0.67) | (0.66) |
| 60 ≤ Price < 80 | 0.90 | 1.44 | 0.53 | 2.41 | 7.60*** | 5.19** | 1.32 | 1.60 | 0.28 |
| | (0.96) | (1.06) | (1.07) | (1.57) | (2.34) | (2.15) | (0.82) | (1.03) | (1.05) |
| 80 ≤ Price < 100 | 0.23 | 1.15 | 0.92 | 1.45 | 0.86 | -0.59 | 0.85 | 1.10 | 0.24 |
| | (0.90) | (1.27) | (1.20) | (0.95) | (1.15) | (1.12) | (0.65) | (1.05) | (1.02) |
| Small Probabilities | 0.26 | -2.93*** | -3.18*** | -0.14 | -2.11 | -1.97* | 0.08 | -2.21** | -2.29** |
| | (0.87) | (1.12) | (1.24) | (0.86) | (1.32) | (1.15) | (0.67) | (0.99) | (1.03) |
| Large Probabilities | 0.17 | 0.96 | 0.78 | 1.71 | 4.47*** | 2.76** | 0.60 | 1.01* | 0.41 |
| | (0.51) | (0.65) | (0.60) | (1.09) | (1.49) | (1.23) | (0.45) | (0.59) | (0.58) |
| Large – Small | -0.08 | 3.88*** | 3.97*** | 1.85 | 6.58*** | 4.73*** | 0.52 | 3.22*** | 2.70** |
| | (0.96) | (1.29) | (1.37) | (1.13) | (1.83) | (1.60) | (0.74) | (1.15) | (1.13) |
| R-squared | 0.0003 | 0.0004 | 0.0004 | 0.0009 | 0.0107 | 0.0018 | 0.0002 | 0.0005 | 0.0004 |
| Expiration Days | 1029 | 1022 | 1034 | 718 | 649 | 722 | 1043 | 1036 | 1044 |
| Observations | 69562 | 95810 | 165372 | 35286 | 4294 | 39580 | 104848 | 100104 | 204952 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

**Table III: Returns to Expiration for Different Securities Sorted by Bid-Ask Spread**

This table reports the results from nine (3x3) ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5 (see text or Table I for details). The nine regressions include three sets of regressions for securities based on one-day sports, financial and all events. Each set includes regressions for high bid-ask spread, low bid-ask spread, and both groups of securities (see text for construction).

| | Sports | | | Financial | | | All | | |
|---|---|---|---|---|---|---|---|---|---|
| | High Spread | Low Spread | Low – High | High Spread | Low Spread | Low – High | High Spread | Low Spread | Low – High |
| 0 < Price < 20 | -0.85 | -3.87*** | -3.02** | -0.42 | -0.49 | -0.06 | -0.47 | -2.21*** | -1.74* |
| | (0.90) | (0.97) | (1.25) | (0.69) | (1.12) | (1.13) | (0.62) | (0.79) | (0.91) |
| 20 ≤ Price < 40 | 1.58 | -2.49 | -4.07* | 0.01 | -2.26 | -2.27 | 0.56 | -2.47 | -3.03 |
| | (1.41) | (2.07) | (2.26) | (1.22) | (2.25) | (2.03) | (0.92) | (1.88) | (1.92) |
| 40 ≤ Price < 60 | -0.50 | 0.26 | 0.76 | 1.37 | 4.52 | 3.16 | -0.29 | 0.30 | 0.59 |
| | (0.53) | (0.69) | (0.65) | (1.45) | (2.82) | (2.55) | (0.49) | (0.68) | (0.65) |
| 60 ≤ Price < 80 | 1.21 | 1.23 | 0.02 | 2.59* | 6.56*** | 3.97* | 1.57* | 1.36 | -0.21 |
| | (0.94) | (1.10) | (1.08) | (1.56) | (2.39) | (2.19) | (0.80) | (1.07) | (1.06) |
| 80 ≤ Price < 100 | 0.35 | 1.10 | 0.75 | 1.39 | 1.09 | -0.31 | 0.86 | 1.09 | 0.23 |
| | (0.88) | (1.35) | (1.27) | (0.95) | (1.19) | (1.17) | (0.64) | (1.10) | (1.07) |
| Small Probabilities | 0.36 | -3.18*** | -3.55*** | -0.21 | -1.37 | -1.17 | 0.04 | -2.34** | -2.39** |
| | (0.88) | (1.14) | (1.28) | (0.86) | (1.36) | (1.25) | (0.68) | (1.02) | (1.09) |
| Large Probabilities | 0.36 | 0.86 | 0.51 | 1.78 | 4.06*** | 2.27* | 0.72 | 0.92 | 0.20 |
| | (0.50) | (0.68) | (0.61) | (1.09) | (1.51) | (1.27) | (0.45) | (0.62) | (0.59) |
| Large – Small | -0.01 | 4.05*** | 4.05*** | 1.99* | 5.43*** | 3.44** | 0.67 | 3.26*** | 2.59** |
| | (0.97) | (1.33) | (1.44) | (1.14) | (1.86) | (1.74) | (0.75) | (1.20) | (1.21) |
| R-squared | 0.0003 | 0.0004 | 0.0003 | 0.0010 | 0.0078 | 0.0015 | 0.0003 | 0.0004 | 0.0003 |
| Expiration Days | 1034 | 1013 | 1034 | 720 | 599 | 722 | 1044 | 1027 | 1044 |
| Observations | 77604 | 87768 | 165372 | 35859 | 3721 | 39580 | 113463 | 91489 | 204952 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

**Table IV: Returns to Expiration for Different Securities Sorted by Information-based Price Movement**

This table reports the results from nine (3x3) ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5 (see text or Table I for details). The nine regressions include three sets of regressions for securities based on one-day sports, financial and all events. Each set includes regressions for high information-based price movement, low information-based price movement, and both groups of securities (see text for construction).

| | Sports | | | Financial | | | All | | |
|---|---|---|---|---|---|---|---|---|---|
| | High Info | Low Info | Low – High | High Info | Low Info | Low – High | High Info | Low Info | Low – High |
| 0 < Price < 20 | -0.70 | -3.99*** | -3.29** | -0.24 | -1.18 | -0.94 | -0.30 | -2.14*** | -1.85*** |
| | (0.95) | (0.98) | (1.34) | (0.68) | (0.78) | (0.58) | (0.61) | (0.62) | (0.59) |
| 20 ≤ Price < 40 | 1.10 | -2.16 | -3.26* | 0.07 | -1.20 | -1.28 | 0.47 | -1.94 | -2.41 |
| | (1.21) | (2.08) | (1.97) | (1.23) | (1.69) | (1.38) | (0.89) | (1.63) | (1.55) |
| 40 ≤ Price < 60 | -0.41 | 0.18 | 0.59 | 1.20 | 3.68* | 2.49 | -0.24 | 0.25 | 0.49 |
| | (0.50) | (0.68) | (0.59) | (1.46) | (2.07) | (1.70) | (0.47) | (0.67) | (0.59) |
| 60 ≤ Price < 80 | 1.05 | 1.36 | 0.30 | 2.31 | 5.79*** | 3.48** | 1.36* | 1.58 | 0.22 |
| | (0.88) | (1.09) | (0.97) | (1.59) | (1.88) | (1.57) | (0.76) | (1.04) | (0.95) |
| 80 ≤ Price < 100 | 0.17 | 1.24 | 1.07 | 0.94 | 2.52*** | 1.58** | 0.54 | 1.56* | 1.02 |
| | (0.92) | (1.24) | (1.16) | (1.03) | (0.73) | (0.80) | (0.68) | (0.94) | (0.91) |
| Small Probabilities | 0.20 | -3.08*** | -3.28*** | -0.08 | -1.19 | -1.11 | 0.09 | -2.04** | -2.13** |
| | (0.82) | (1.13) | (1.16) | (0.86) | (1.06) | (0.76) | (0.65) | (0.90) | (0.84) |
| Large Probabilities | 0.27 | 0.92 | 0.65 | 1.48 | 4.00*** | 2.51**** | 0.55 | 1.13* | 0.58 |
| | (0.49) | (0.66) | (0.57) | (1.12) | (1.15) | (0.85) | (0.44) | (0.58) | (0.53) |
| Large – Small | 0.07 | 4.00*** | 3.93*** | 1.57 | 5.19*** | 3.63*** | 0.46 | 3.17*** | 2.71*** |
| | (0.91) | (1.31) | (1.31) | (1.16) | (1.39) | (1.12) | (0.73) | (1.07) | (0.96) |
| R-squared | 0.0002 | 0.0004 | 0.0003 | 0.0007 | 0.0063 | 0.0016 | 0.0002 | 0.0005 | 0.0003 |
| Expiration Days | 1034 | 1021 | 1034 | 716 | 694 | 722 | 1044 | 1038 | 1044 |
| Observations | 76568 | 88804 | 165372 | 32079 | 7501 | 39580 | 108647 | 96305 | 204952 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

**Table V: Returns to Expiration for High Noise Trade Securities Sorted by Noise Trade Persistence**

This table reports the results from three ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5 (see text or Table I for details). Each regression includes only high noise trade securities based on one-day sports and financial events. The three regressions include either securities with sporadically high noise trade, persistently high noise trade or both groups of securities (see text for construction).

| | Sporadic Noise Trade | Persistent Noise Trade | Persistent – Sporadic |
|---|---|---|---|
| 0 < Price < 20 | -1.15 | -6.36*** | -5.21*** |
| | (0.80) | (1.09) | (1.21) |
| 20 ≤ Price < 40 | -1.51 | -6.17 | -4.66 |
| | (1.30) | (5.34) | (4.99) |
| 40 ≤ Price < 60 | 0.00 | 1.05 | 1.05 |
| | (0.51) | (1.33) | (1.16) |
| 60 ≤ Price < 80 | 1.24 | 2.29 | 1.04 |
| | (0.82) | (1.81) | (1.50) |
| 80 ≤ Price < 100 | -0.37 | 5.02** | 5.38*** |
| | (0.96) | (2.07) | (1.95) |
| Small Probabilities | -1.33* | -6.27** | -4.94** |
| | (0.79) | (2.66) | (2.52) |
| Large Probabilities | 0.29 | 2.78*** | 2.49*** |
| | (0.48) | (1.10) | (0.94) |
| Large – Small | 1.62* | 9.05*** | 7.43*** |
| | (0.91) | (2.91) | (2.73) |
| R-squared | 0.0002 | 0.0022 | 0.0008 |
| Expiration Days | 1036 | 783 | 1036 |
| Observations | 69690 | 30414 | 100104 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

**Table VI: Returns to Expiration for High Noise Trade Securities Sorted by Imbalance, News, Volume and Horizon**

This table reports the results from 12 (4x3) ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5 (see text or Table I for details). Each regression includes only high noise trade securities based on one-day sports and financial events. There are four sets of regressions, each including securities with high noise trader influence, low noise trader influence, and both groups of securities. The four proxies for noise trader influence are high order imbalance, a lack of news, high trading volume, and a long time horizon (see text for details). The table displays only the Wald tests that summarize the coefficient estimates (see Figure 4 for the coefficients).

| Panel A | Imbalance | | | News | | |
|---|---|---|---|---|---|---|
| | Low | High | High – Low | Some | None | None – Some |
| Small Probabilities | -1.58 | -2.49* | -0.92 | -1.54* | -4.12*** | -2.58* |
| | (1.10) | (1.29) | (1.38) | (0.90) | (1.38) | (1.36) |
| Large Probabilities | 0.22 | 1.57** | 1.35** | 0.99* | 1.06 | 0.07 |
| | (0.70) | (0.68) | (0.68) | (0.54) | (0.81) | (0.70) |
| Large – Small | 1.80 | 4.07*** | 2.27 | 2.52** | 5.17*** | 2.65* |
| | (1.24) | (1.49) | (1.53) | (1.00) | (1.62) | (1.52) |
| R-squared | 0.0003 | 0.0013 | 0.0009 | 0.0006 | 0.0006 | 0.0006 |
| Expiration Days | 1019 | 1026 | 1036 | 1018 | 1006 | 1030 |
| **Panel B** | **Volume** | | | **Horizon** | | |
| | Low | High | Low – High | Expiry Day | Earlier Day | Earlier – Expiry |
| Small Probabilities | -1.70 | -3.00** | -1.30 | -1.91** | -4.05** | -2.14 |
| | (1.25) | (1.34) | (1.54) | (0.91) | (1.88) | (1.83) |
| Large Probabilities | 0.30 | 1.51* | 1.20 | 0.79 | 1.44 | 0.65 |
| | (0.80) | (0.78) | (0.91) | (0.60) | (1.14) | (1.19) |
| Large – Small | 2.00 | 4.51*** | 2.51 | 2.70** | 5.49*** | 2.79 |
| | (1.47) | (1.56) | (1.78) | (1.05) | (2.08) | (1.93) |
| R-squared | 0.0001 | 0.0012 | 0.0006 | 0.0004 | 0.0009 | 0.0006 |
| Expiration Days | 1019 | 1012 | 1036 | 1011 | 878 | 1036 |
| Observations | 41613 | 58491 | 100104 | 65940 | 34164 | 100104 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

**Table VII: Realizable Returns to Expiration for High Noise Trade Securities**

This table reports the results from six ordinary least squares (OLS) regressions of securities' returns to expiration on five dummy variables, Price1 through Price5. The regressions and results are identical to Table I except that the dependent variable is now realizable returns to expiration rather than returns to expiration. Thus, there are two separate regressions for the buyer's and the seller's realizable returns to expiration in this table corresponding to each regression in Table I. I assume that the buyer pays the inside ask price, the seller receives the inside bid price in the computation of realizable returns to expiration, and both buyers and sellers must pay 0.8%, the round-trip commission for a market order on the TradeSports exchange. See Table I for further details.

| | Sports | | Financial | | All | |
|---|---|---|---|---|---|---|
| | Buyer | Seller | Buyer | Seller | Buyer | Seller |
| 0 < Price < 20 | -4.92*** | 2.14** | -2.37** | -1.32 | -3.57*** | 0.31 |
| | (1.01) | (1.05) | (1.05) | (1.05) | (0.76) | (0.79) |
| 20 ≤ Price < 40 | -3.77* | 0.89 | -5.83*** | 1.56 | -3.99** | 0.96 |
| | (2.03) | (2.03) | (2.22) | (2.22) | (1.81) | (1.82) |
| 40 ≤ Price < 60 | -1.13* | -1.68** | 2.98 | -6.92** | -1.08 | -1.74*** |
| | (0.67) | (0.67) | (2.79) | (2.79) | (0.67) | (0.67) |
| 60 ≤ Price < 80 | 0.04 | -2.83*** | 5.60** | -9.61*** | 0.19 | -3.01*** |
| | (1.06) | (1.06) | (2.35) | (2.34) | (1.03) | (1.03) |
| 80 ≤ Price < 100 | -0.27 | -2.57** | -0.80 | -2.51** | -0.37 | -2.56** |
| | (1.27) | (1.27) | (1.16) | (1.15) | (1.05) | (1.05) |
| Small Probabilities | -4.35*** | 1.51 | -4.10*** | 0.12 | -3.78*** | 0.63 |
| | (1.11) | (1.12) | (1.32) | (1.32) | (0.98) | (0.99) |
| Large Probabilities | -0.45 | -2.36*** | 2.59* | -6.35*** | -0.42 | -2.43*** |
| | (0.65) | (0.65) | (1.49) | (1.48) | (0.60) | (0.59) |
| Large – Small | 3.89*** | -3.87*** | 6.69*** | -6.47*** | 3.36*** | -3.07*** |
| | (1.28) | (1.29) | (1.83) | (1.83) | (1.15) | (1.16) |
| R-squared | 0.0008 | 0.0017 | 0.0098 | 0.0172 | 0.0009 | 0.0019 |
| Expiration Days | 1022 | 1022 | 649 | 649 | 1036 | 1036 |
| Observations | 95810 | 95810 | 4294 | 4294 | 100104 | 100104 |

Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

**Figure 1: The Effect of Noise Trade on Returns to Expiration**

This figure displays the estimated differences between the returns to expiration of securities with differing degrees of noise trade for five equally-spaced pricing categories. Thus, the figure plots the three sets of coefficient estimates on the five pricing category interaction terms shown in Columns Three, Six and Nine in Table II (see table for construction). These three sets of interaction terms measure the effect of noise trade in sports, financial and all securities. Each interaction term is equal to the returns to expiration of high noise trade minus low noise trade securities.

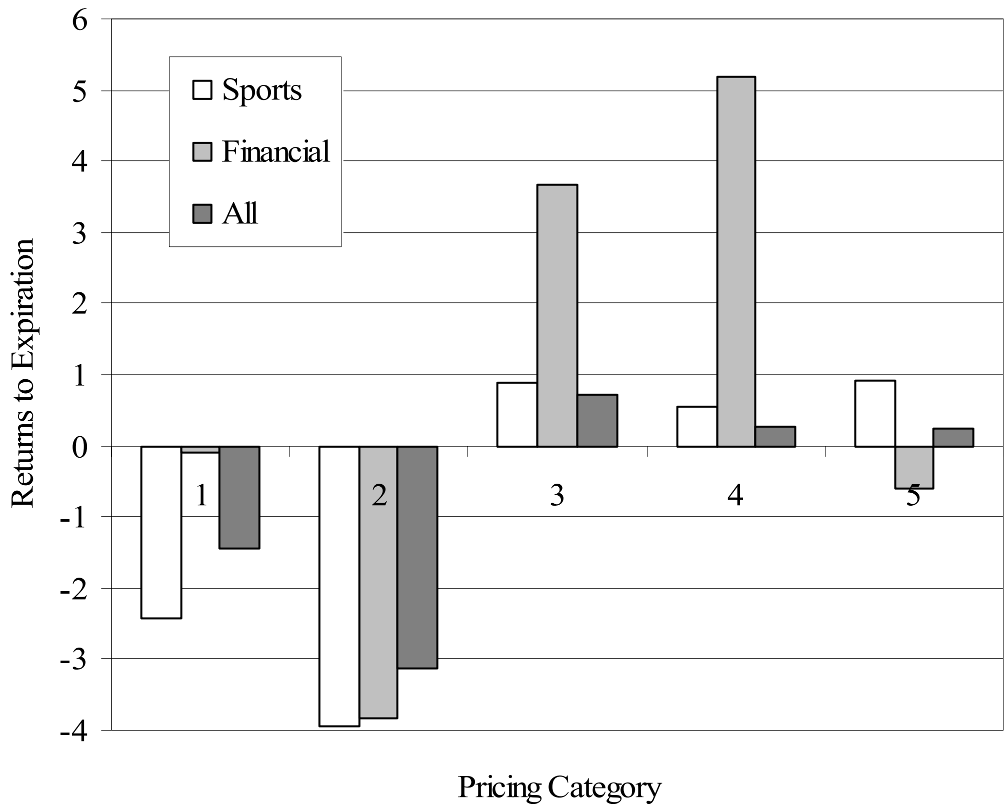

**Figure 2: Robustness of the Effect of Noise Trade on Returns to Expiration**

This figure depicts the estimated differences between the returns to expiration of securities with differing degrees of noise trade as measured by two liquidity proxies—bid-ask spreads and information-based price movements—for five equally-spaced pricing categories. Thus, the figure plots the four sets of coefficient estimates on the five pricing category interaction terms shown in Columns Three and Six of Tables III and IV (see these tables for construction). These four sets (2x2) of interaction terms measure the effect of spreads and information-based price movement in sports and financial securities. For spreads, the interaction term is equal to the returns to expiration of low spread minus high spread securities. For information-based price movement, the interaction term is equal to the returns to expiration of low-info minus high-info securities.

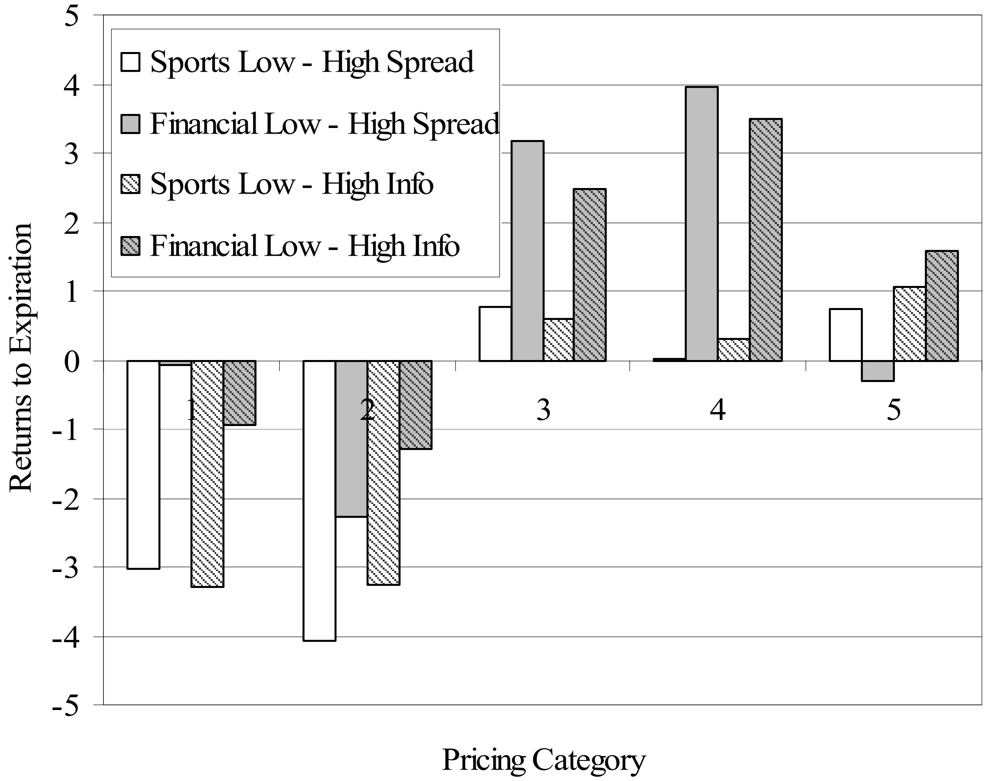

**Figure 3: The Effects of Sporadic and Persistent Noise Trade on Securities**

This figure depicts the estimated returns to expiration of securities with no noise trade, sporadic noise trade, and persistent noise trade for five equally-spaced pricing categories. Thus, the figure plots the three sets of dummy coefficient estimates on the five pricing category interaction terms shown in Column Seven in Tables II and Columns One and Two in Table V (see these tables for construction). All regressions include both sports and financial securities.

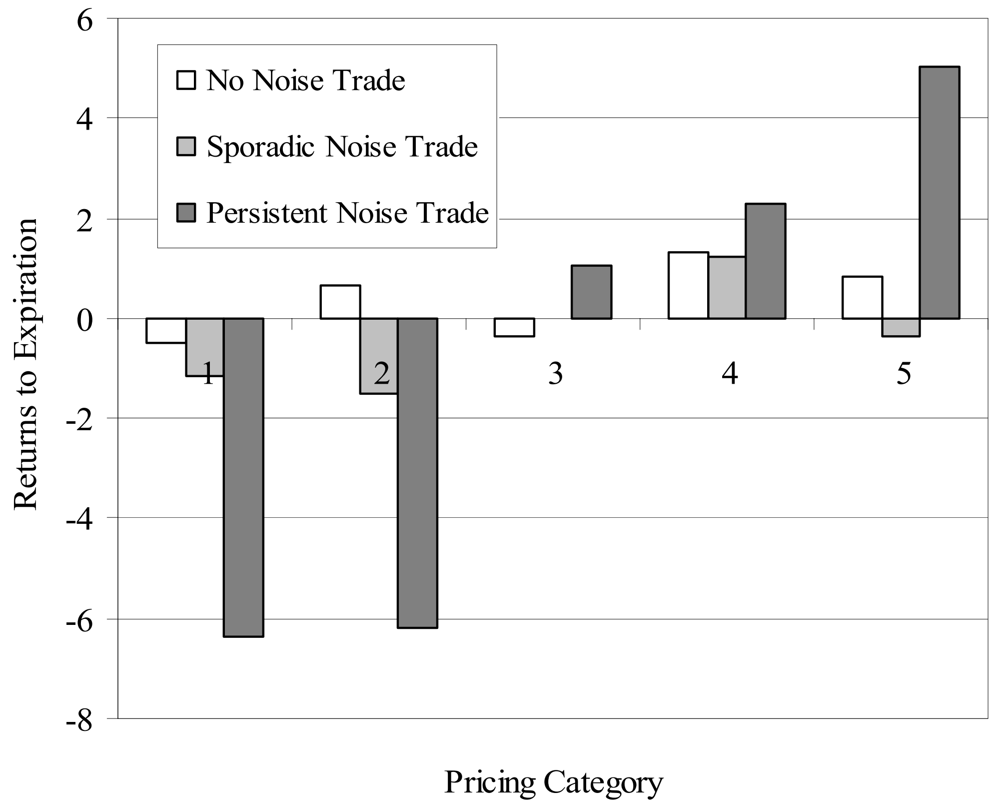

**Figure 4: The Effects of Imbalance, News, Volume, and Horizon on High Noise Trade Securities**

This figure shows the estimated differences between the returns to expiration of high noise trade securities with differing degrees of noise trader influence as measured by four proxies—high order imbalance, a lack of news, high trading volume, and a long time horizon—for five equally-spaced pricing categories. Thus, the figure plots the four sets of coefficient estimates on the five pricing category interaction terms from the regressions in Columns Three and Six of Panels A and B in Table VI (see table for construction). These four sets of interaction terms measure the effect of high order imbalance, a lack of news, high trading volume, and a long time horizon on the returns to expiration of high-noise securities. Each regression includes all of the sports and financial securities that qualify as having high noise trade (see text for details).

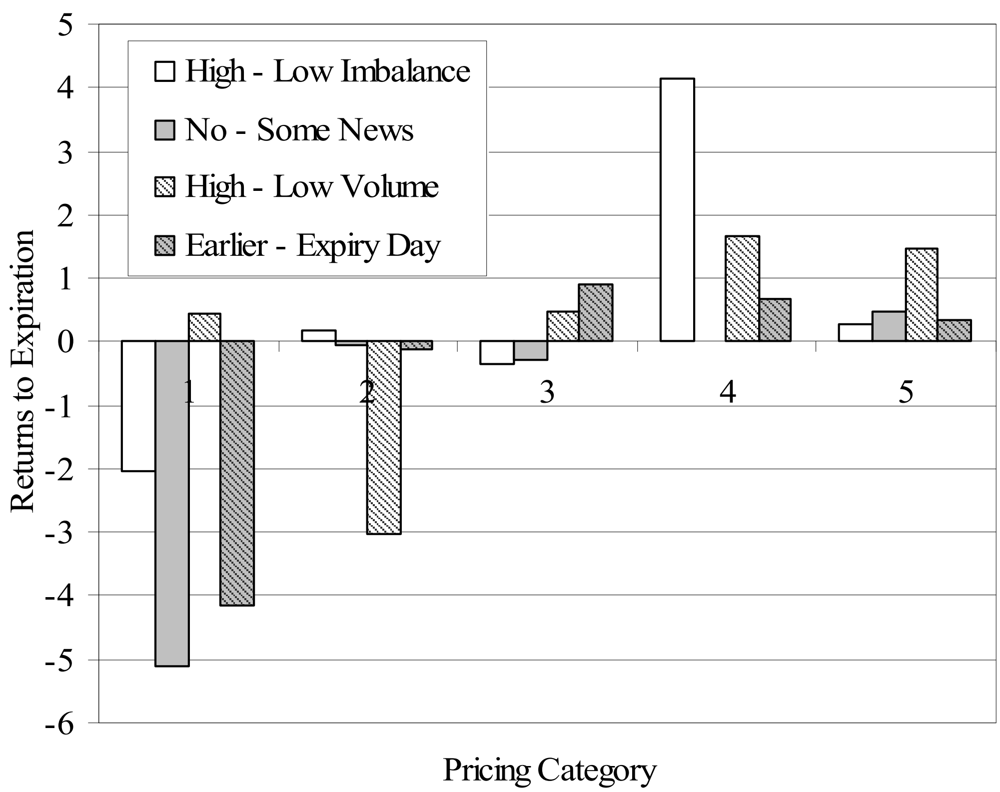

**Figure 5: Profitability of Trading in High Noise Trade Securities of Different Types**

This figure shows the realizable returns to expiration for buyers and sellers of sports and financial securities in each of the five pricing categories. Each line represents one of the four sets of coefficient estimates for the five pricing category dummies. The numerical estimates appear in Columns One through Four in Table VII (see table for further details).