Deafened by Noise:

Do Noise Traders Affect Volatility and Returns?

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Abstract

This paper investigates the relation between noise traders' activities and daily price volatility. Building on Black's (1986) seminal work, we investigate whether noise traders introduce additional risk into stock prices by increasing volatility. In addition, we test whether noise traders increase returns. Our results show that the noise traders' behavior has a significant positive effect on the daily stock price volatility but not on the returns. Furthermore, it is found that small cap stocks with the strongest limits to arbitrage are affected by noise traders the most. Our paper has also normative implications for policy makers.

JEL: G12, G14.

Keywords: Information; Noise trading; Limits to arbitrage; Market efficiency; Volatility

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1. Introduction

In a paper published in the *Journal of Finance* in 1986, Fisher Black introduced the concept of noise traders and offered a theoretical formulation of how this group of traders affects the market. In turn, the current study tests empirically how noise traders' activities influence stock price dynamics. More specifically, by utilizing a unique dataset from the Australian Stock Exchange (ASX), we investigate whether noise trading increases volatility as predicted by theoretical models (Black, 1986, DeLong et al., 1990, Campbell and Kyle, 1993 and others). In addition, we examine whether noise traders increase returns. In line with Black (1986), noise traders are defined as non-fundamental traders who either trade on noisy information or simply for the sake of trading.

Classical financial theories are based on the efficient market hypothesis. These theories assume that market participants are rational and hence prices react only to new fundamental information. However, over the past couple of decades evidence has relentlessly surfaced putting the assumption of investor rationality to question. The existence of noise traders could potentially explain some of the anomalies and puzzles observable in the marketplace, such as positive feedback trading (Kurov, 2008), price bubbles (DeLong et al., 1990) and excess volatility (Shiller, 1981).

Investigating the relation between noise trading activity and daily volatility and returns is important for the following reasons. First, studying the effect that noise traders have on stock price volatility is important from an academic point of view. The literature offers inconclusive views on this issue. The first and most accepted of them is that noise traders by acting on information that does not reflect any fundamental value will add additional volatility on top of what can be explained rationally (Black, 1986; DeLong et al., 1990; Campbell and Kyle, 1993;

and others). Conversely, consistent with the liquidity and volatility literature is the view that noise traders being suppliers of liquidity will make markets more deep, thus helping to decrease volatility.[1] The few empirical studies of this interdependence are mixed. The current study sheds new light on this relation and is the first to do so by incorporating a direct proxy of noise trading based on dispersion in net initiated order flows at daily frequency.

Second, understanding what impact noise traders have on stock price volatility has economic significance, as it allows investors to make more informed portfolio allocation decisions. Dumas et al. (2007) devise a model which shows that increased volatility caused by irrational traders who change their expectations too often, can have a negative effect on rational traders' optimal investment strategies. Understanding whether noise traders affect excess volatility and, if so, where their impact is the strongest, will allow investors to construct an optimal portfolio to suit their risk – return preferences. For example, conservative fund managers will prefer to override their portfolios with stocks that are less likely to display excess volatility. If a positive relation between noise trading and volatility is observed, such stocks would be those that are less likely to attract noise traders.

Finally, examining the relation between noise trading and volatility and returns is of interest to policy makers. Rose and Jeanne (1999) note that regulatory regimes differ predominantly due to the noisiness of the specific markets. The general preconception is that noise traders contribute to excess volatility, with some authors (Summers and Summers, 1989; Shleifer and Summers, 1990) arguing that policy makers should implement measures that reduce the level of noise

[1] Baker and Stein (2004) and Berkman and Koch (2007) find a positive relationship between liquidity and noise trading. Copeland and Galai (1983), Admati and Pfleiderer (1988), Foster and Viswanathan (1990), Handa and Schwartz (1996), and others find negative relation between liquidity and volatility.

trading in order to enhance the welfare of the community. Through a deeper evaluation of the effect that noise trading has on daily volatility and daily returns, as well as where this relation is strongest, this study allows policy makers to target the problem more accurately.

The paper contributes to the current literature in a number of ways. First, it examines the debated topic of what effect noise traders have on stock price volatility. More specifically, it provides strong support for the theoretical prediction formulated by Black (1986) that noise traders increase the level of volatility. We do so by utilising a daily proxy of noise trading based on intra-day information (Berkman and Koch, 2007). Given that noise traders trade on noisy information as opposed to fundamental information, their effect on the market is more likely to be observed at shorter time periods. Other studies which have explicitly explored the relation between noise trading and volatility (Verma and Verma, 2007; Kurov, 2008) use a proxy based on investors' sentiment and, therefore, are constrained to longer time horizons (monthly and weekly). By employing a direct proxy for noise trading, we are able to measure the relation between noise trading activity and volatility over shorter time periods, where the relation is expected to be strongest.

Second, we test the prediction put forward by DeLong et al. (1990) and Campbell and Kyle (1993) that noise traders have a positive effect on returns. This examination provides insights to the question whether the risk, introduced by noise traders in the form of higher volatility, translates to higher returns. The use of daily data enables us to measure the effect that noise traders have on returns more accurately than that of prior literature (Lee et al., 2002).

Third, we also explore how the relation between noise trading activity and volatility differs across market capitalisations. Therefore, it answers the question of whether some firms are affected to a greater extent by noise traders than other. Given that limits to arbitrage differ between firm sizes, the study will be important to policy makers. Understanding how limits to arbitrage affect the relation between noise trading activity and volatility helps authorities in devising measures that will curb out any undesirable effects that noise traders have on market efficiency.

We find that in line with the predictions of Black (1986) and DeLong et al. (1990), noise traders have a positive effect on daily stock price volatility. However, contrary to DeLong et al. (1990) and Campbell and Kyle (1993), this additional risk introduced by noise traders is not priced in the form of higher returns. In other words, noise trading activity does not have a statistically significant effect on returns. We also observe that noise traders have the strongest effect on the price volatility of small cap stocks that have the highest limits to arbitrage. Our results indicate that noise traders introduce excessive volatility into the market and thus reduce the price discovery process, therefore warranting the introduction of measures which will curb the influence that this category of investors can have on the market. Given that the impact of noise traders is greatest in small cap stocks, which has the highest limit to arbitrage, our finding implies that policy makers should look at policies that will reduce limits to arbitrage and thus limit the negative effect on the market of noise traders.

The remainder of this paper is organized as follows. Section 2 summarizes the relevant literature and develops the hypotheses. Section 3 discusses the data utilized. Section 4 presents the empirical results obtained. Finally, Section 5 concludes the paper with a summary of major findings.

2. Literature Review

2.1 Who are Noise Traders?

Black (1986) describes noise traders as traders who "*trad[e] on noise as if it were information*". The predominant attribute of noise traders according to Black (1986) is that they trade due to psychological barriers or simply according to their taste for trading. The definition implies that noise traders act on noisy information which is not based on fundamentals. The idea behind noise trading, as put forward by Black (1986), is that noise traders by acting on information that is not truly 'information' will distort the true price of the underlying asset. This distortion will be interpreted as information by other noise traders, who will act on it, adding further noise to the stock price.

There is nonetheless, an ambiguity as to who exactly is an informed as opposed to a noise trader. Based on the 'stealth trading' hypothesis, Chakravarty (2001) documents that institutions are the informed traders. Kurov and Sancetta (2005), studying large and small trades in the futures market also conclude that retail traders are noise traders, while institutional investors are informed traders. However, Willman et al. (2006) find that institutional investors are not always rational and often engage in noise trading activities. Their paper is based on the survey responses of 118 traders in four large investment banks. The authors find that many institutional traders, do not trade rationally. Some motivations behind trading include boredom, attention seeking and to accelerate learning. Therefore, it is difficult to classify groups of investors as either information or noise traders. According to Black (1986), the distinction between information and noise traders will always be ambiguous, given the uncertain nature of financial markets.

2.2 Noise Trading and Volatility

DeLong et al. (1990) predict that in the presence of noise traders and limits of arbitrage, returns will be excessively volatile – meaning that prices move more than can be explained on the basis of changes in fundamental value. This is consistent with the hypothesis put forward by Black (1986), that an increase in noise trading will increase short term volatility. Consistent with the literature (Black, 1986; DeLong et al., 1990), Campbell and Kyle (1993) develop a theoretical model of the price formation process, which predicts that noise trading leads to overreaction to fundamental information, and hence excessively high volatility. Danthine and Moresi (1993) further argue that more information will mean less volatility as improved information places rational agents in a better position to counteract. However, like the other models, the authors hypothesize that in the absence of new information, more noise will increase the level of short term volatility.

A competing body of literature is based on the relation between liquidity and volatility. Black (1986) predicts that noise traders, despite having a negative effect on the price discovery process are nonetheless an essential component of the market due to supplying liquidity. Baker and Stein (2004) show that noise traders have a positive effect on liquidity. In the presence of short sale restrictions, they argue that the market will be dominated by irrational traders, who under-react to information contained in order flows thus boosting liquidity.

Although there has been a reasonable amount of research conducted, into the effect that noise trading has on liquidity (Berkman and Koch, 2007; Bloomfield et al., 2007) and informational efficiency (Bloomfield et al., 2007; Kurov, 2008), the relation between noise trading and daily volatility has been relatively sparse. Koski et al. (2004) was the first to directly tackle this question. Based on a large sample of NASDAQ stocks during the 3rd quarter of 1999 and an indirect proxy of noise trading, based on stock message board activity, the authors find evidence to support the notion that noise trading increases volatility. Moreover, Koski et al. (2004) find that volatility generates increases in future message board posting even more strongly than messages generate future volatility.

Foucault et al. (2008) also address the relation between noise trading and volatility. Classifying individual traders as noise traders, their paper documents that after a reform that makes short selling or buying on margin more expensive for individual investors relative to institutions, the volatility of the stocks that are affected by this reform declines relative to the volatility of other stocks. This finding suggests a positive relation between noise trading and volatility.

Contrary to the findings of Koski et al. (2004) and Foucault et al. (2008), Verma and Verma (2007) observe a negative relation between noise trading and volatility. The authors use a modified version of the Brown and Cliff (2005) proxy for noise trading in the form of investor sentiment. Verma and Verma (2007) distinguish between rational and irrational sentiments of both individuals and institutions. The authors conclude that individual investor sentiment reacts to institutional investor sentiment but not vice versa and that a significant negative relation exists between irrational sentiment and volatility. Building on Brown and Cliff's (2005) study, Kurov (2008) also documents that high investor sentiment has a negative effect on the transitory volatility in the futures market. These findings could be explained by the fact that monthly and weekly volatilities were used. Noise traders can be expected to have the strongest effect in the short term, whereas over longer time horizons the liquidity they supply will smooth out any effect on volatility. Therefore, the first hypothesis stated in the alternate form is specified as follows:

$H1$: *The noise trading activity is positively related to daily volatility.*

2.3 Noise Trading and Returns

DeLong et al. (1990) in their paper propose that the additional risk that noise traders introduce into stock prices is priced in the form of higher returns. The authors argue that because of the additional risk that noise traders induce, sophisticated but risk averse arbitrageurs will hold lower portions of the stock than they would without the presence of noise traders. Therefore, any additional returns will mainly flow to noise traders who, after all, introduce and bare the additional risk in the first place. The authors hypothesize that noise traders will reap the rewards of their actions if they are on average bullish, and will suffer losses if they are on average bearish.

Campbell and Kyle (1993), develop a similar theoretical model to explain the price formation process after accounting for noise traders. Consistent with DeLong et al. (1990), the authors argue that noise traders are able to move stock prices due to informed investors risk aversion. They claim that because noise traders lead to the overreaction of fundamental information, the stock price returns will also be greater than the returns explained by fundamental values. However, because prices will revert to fundamental values in the long term, any short term positive (negative) returns will be accompanied by longer term negative (positive) returns. Therefore, if noise traders do affect stock prices, the greatest effect will be on short term returns.

A number of studies have attempted to test the hypothesis put forward by DeLong et al. (1990) and Campbell and Kyle (1993). Lee et al. (1991) use the fluctuations in closed - end fund discounts as a proxy of investor sentiment. They find a high correlation between the closed end-fund discounts and returns of small capitalization stocks. Kelly (1997) on the other hand, uses the number of low income households to proxy for noise trader participation in the market. The assumption underlying the proxy is that the probability of an investor being a noise trader diminishes with income. In line with DeLong et al. (1990), Kelly (1997) finds that a higher participation of low income households is associated with a lower participation by high income households.

Using a survey based measure of investor sentiment, Brown and Cliff (2005) find weak short-run returns predictability, but find a strong correlation between long horizons sentiment and returns. Their results put in question Black's (1986) and DeLong et al's. (1990) prediction that the noise traders' effect will be minimal in the long term due to the presence of arbitrageurs who will help prices revert to equilibrium levels in the long term. Lee et al. (2002) use a GARCH framework and measures of investor sentiment to proxy for noise trading direction. In line with DeLong's et al. (1990) prediction, they find a positive relation between sentiment and excess returns. The empirical results in the literature are, hence, very mixed. Based on the strong theoretical expectations, the second hypothesis stated in the alternate form is specified as follows:

$H2$: *The noise trading activity is positively related to daily stock returns.*

2.4 Firm Size and Limits to Arbitrage

Black (1986) was the first to introduce the concept of noise trading in a theoretical framework. In his now seminal paper, Black (1986) put forward a generalized model of how noise, defined as anything that makes observations imperfect, can distort the price of an asset away from its true value.

Black puts forward the argument later expanded by DeLong et al. (1990) that the price of a stock tends to move towards its fundamental value over time, as information traders offset the effect of irrational noise traders. The effectiveness of informed traders or arbitrageurs in ensuring that prices revert to fundamental values has been questioned by the limits of arbitrage theory (see amongst others DeLong et al., 1990; Shleifer and Summers, 1990; and Shleifer and Vishny, 1997).

DeLong et al. (1990) build further on Black's general model. The authors examine assertions by Friedman (1953) and Fama (1965) that noise trading does not distort the market price of assets over the medium to long term, due to the presence of rational arbitrageurs, who drive prices back towards fundamental value. The authors also develop a model, which shows how risk averse arbitrageurs will be hesitant to hold large positions in the presence of the risk that noise traders generate and will push prices further away from the fundamental levels (noise trader risk). The noise trader risk according to the authors, significantly reduces the efficiency of arbitrageurs in ensuring that prices revert to fundamental values.

There is a large body of literature which argues that short sale restrictions also play a role in limiting arbitrage opportunities. Authors such as Cornell and Liu (2001), Lamont and Thaler (2003), and Schill and Zhou (2001) study the effect that short sale restrictions have on market efficiency. They find that strong demand, coupled with short sale restrictions result in irrationally high prices. There are a number of ways in which short selling may be constrained, with the most obvious being, having restrictively high short lending fees. Short lending fees are determined by the supply and demand for the stock in the stock loan market. Such costs are hence more likely to be excessively high for small cap stocks which tend to be less liquid. Furthermore, Boehme et al. (2002) argue that stocks with no derivative products will be more expensive to short as they do not allow for investors to create positions in the derivative market equivalent to short selling. Once again, such stocks are more likely to be small cap stocks. This view is supported by the empirical study of Jones and Lamont (2002), who find that small stocks are generally more expensive to short.

Mitchell et al. (2002) on the other hand, find that the single most important limit to arbitrage is the cost associated with information gathering. Payoffs from engaging in arbitrage activities are uncertain. Arbitrageurs therefore, will be unwilling to engage in risky activities when the costs associated with information gathering are excessively high. Given that small firms are generally less covered by analysts than large cap stocks (Hong et al., 2000), it can be assumed that the costs associated with acquiring information on fundamental values will be larger for small cap stocks. Once again, it would appear that limits to arbitrage caused by information gathering costs will be strongest for small cap stocks. Therefore, the third hypothesis stated in the alternate form can be specified as follows:

> $H3$: *The correlation between noise trading activity and daily volatility (returns) is stronger for small cap stocks in comparison to large cap stocks.*

3. Data and Methodology

IRESS data are utilized for this study.[2] The data provide information on all intraday transactions: date and time to the nearest second, transaction price, trading volume, buy/sell direction as well as the name of the buying and selling brokers involved in the transaction. This dataset allows for the calculation of the measure of noise trading suggested by Berkman and Koch (2007). Stock price data and market capitalization for the entire set of shares listed on the ASX is obtained for the period between the start of March 2006 and the end of February 2008. For any stock, a day

[2] IRESS is a data provider for a broad range of financial markets professionals across Australia, New Zealand and Canada.

is treated as a 'trading day' if there are at least four distinct brokers who initiate trades during that trading session (Berkman and Koch, 2007). In line with Berkman and Koch (2007), to account for thin trading and trading halts, stocks which were not traded for at least 80 percent of time during the sample period are taken out of the sample. Furthermore, preference shares and unit trusts will be excluded from the sample. After filtering, the sample comprises of 317 stocks. The average number of trading days for each stock under investigation during the sample period is 480.

In addition to IRESS data, we also utilize the market depth data provided by SIRCA, which detail the best bid and as quotes in the limit order book. We use this dataset to calculate the daily bid-ask spread, which is the average of the difference in bid and ask prices across all intraday observations, where a change in the best quotes in the book was reported. The daily spread is used in the current study as one of the control variables when investigating the relation between noise trading and volatility.

Calculating Measure of Noise Trading

Consistent with Berkman and Koch (2007) the standardized dispersion of net initiated order flows across brokers (NIOF) proxies for the level of noise trading. This proxy of noise is based on the assumption that noise traders trade randomly, and hence an increase in the trading activity of noise traders translates into a greater dispersion in net initiated order flows across brokers. NIOF is standardized by broker market share to account for the fact that brokers with greater market share will have higher NIOF's. It is assumed that market share can be measured by each broker's standard deviation in NIOF over the sample period, where larger brokers have a greater standard deviation than smaller brokers.

To ensure the results are robust a number of alternate standardization procedures are utilized. The first measure accounts for differences in each broker's market share by dividing each broker's daily NIOF for a particular firm by that broker's standard deviation in the NIOF for that firm over the sample period. The daily noise trading activity is then calculated as the standard deviation of all brokers daily standardized NIOF.

The second measure uses a different standardization procedure. As for the first measure it is assumed that NIOF is influenced by each broker's market share. However, for the second measure, it is assumed that the market share should be calculated as the brokers total market share for all stocks, as opposed to the market share for a particular stock. Therefore, each broker's daily NIOF for a particular firm is divided by the standard deviation in that broker's daily NIOF across all firms over the sample period.

Finally, it is possible that the presence of small brokers that do not initiate many transactions over the sample period will distort the results. This is because such small brokers will display abnormally low standard deviations and hence excessive large standardized NIOF's. To deal with this potential problem of outliers, small brokers, defined as those that initiated transactions on less that 30 days over the sample period, are grouped together. These grouped brokers are treated as one large broker. The average number of small brokers in our sample is 4.

4. Empirical Results

4.1 Descriptive Statistics

Table I provides descriptive statistics on daily returns, daily volatility as well as daily noise trading measures. Panel A, of Table I reports daily returns and liquidity summary statistics. The panel shows that average daily returns for sample stocks over the sample period are negative.

This finding is unsurprising given that the sample period is between March 2006 and February 2008, a period when the adverse effects of the subprime crisis together with rising crude oil prices began to kick in. The time series of daily returns appears to be non – normal, leptokurtic and serially correlated. This can be seen from a skewness measure greater than 0, and kurtosis greater than 3. Panel A, of Table I also reports limited evidence of serial correlation in returns, with the Ljung-Box Q-statistic rejecting the null hypothesis of no autocorrelation in 26% of the cases at the 5% significance level.

The large variability in price and liquidity measures reported in Panel A, of Table I, is indicative of the fact that a very wide cross section of firms is utilized in this study, ranging from small cap stocks, through medium cap firms up to the large cap firms.

Panel B provides the descriptive statistics for different estimates of volatility employed in this study – both conditional and unconditional. The summary statistics in Panel B show that the distribution of the volatility proxies departs from the normal distribution. The results in Panel B also indicate strong serial correlation for all daily volatility measures. This conclusion is based on the Ljung– Box Q-statistic, which tests the null of no autocorrelation of variable X up to lag k. Serial correlation in daily volatility exists as the Ljung Box Q-statistic rejects the null hypothesis of no autocorrelation up to lag twelve and twenty four, for over 90% of the sample stocks at the 5% significance level. The weakest evidence of autocorrelation exists for the daily squared returns measure, where in only 68% and 79% of stocks the null hypothesis is rejected at lag 12 and 24, respectively.

Panel B, of Table I justifies the use of alternate measures of volatility employed in this paper, as the different estimates yield considerably different variance measures. An examination of median levels of volatility, reveals that conditional measures tend to be overstated compared with unconditional measures. The GARCH (1,1) model predicts the highest level of volatility, while the daily squared returns the lowest. Given the general inefficiency of daily squared returns as a measure of volatility this is to be expected (Martens and van Dijk, 2006).

Panel C reports the alternate measures of noise trading employed in this paper. A study of the table reveals that all measures of noise are non – normally distributed. The measures are not affected greatly by grouping smaller brokers together. Measure 1 (standardization scheme based on dispersion in NIOF over time for individual firms) after grouping smaller brokers together appears to be the best, as it is closest to following a normal distribution. This measure is primarily used in this paper.

Panel D reports the daily returns, daily volatility, noise trading and liquidity measures across the three firm size subsamples. The percentile classification scheme is used to classify firms into subgroups, where the top 25 percentile of the sample is regarded to be large cap stocks, and the bottom 25 percentile classified as small cap stocks. Panel D reveals that for all firm size segments, the daily returns are on average negative. The small firm subsample however, displays the most negative average daily returns. Similarly, for all volatility measures with the exception of GARCH(1,1), small firms display higher daily volatility than medium and large firms over the sample period. Volatility tends to be lowest for large cap stocks. This is in line with Berkman and Koch (2007), who find that price sensitivity is greatest for less liquid stocks, which can be expected to be the smaller stocks.

The summary statistics provided in Panel D, of Table I show that noise trading is most prevalent for the large cap sample, slightly smaller for the medium cap sample and lowest for the small cap sample. This can be explained by large firm visibility. Noise traders are most likely to concentrate their trades on the more visible firms. This is because such firms are better known to this unsophisticated group of investors. Furthermore, a greater analyst following amongst the large firms leads to the existence of more noisy information. In line with expectations, small firms are found to have lower liquidities than large cap firms, evidenced by lower daily trading volumes and lower number of transactions.

[Insert Table I here]

4.2 Noise Trading and Volatility

Given the evidence of kurtosis in returns reported in the previous subsection, the GARCH (1,1) methodology has been incorporated in this study. This choice is justified given that GARCH type models are better able to deal with the characteristics of stock price dynamics, such as leptokurtic returns, volatility clustering, and serial correlation (Bollerslev et al., 1992). The following model specification is used to test the relation between noise trading and volatility:

$$r_t = \mu + \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim \text{i.i.d.}(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \theta \text{NOISE}_t + \varphi \text{SPREAD}_{t-1} + \vartheta \text{VOL}_{t-1}, \quad (1)$$

In Equation (1), ω is a constant; NOISE_t is the measure of noise trading on day t; SPREAD_{t-1} is the previous days bid – ask spread; and VOL_{t-1} is the previous day's trading volume and σ_t^2 is the conditional variance of the error term process ε_t, which follows a student t - distribution. Daily spread is based on the best quotes in the limit order book, and is calculated as the simple average of the difference in bid and ask prices across all intraday observations, where a change in the best quotes in the book was reported. Trading volume is the sum of buyer-initiated plus seller-initiated trades on a particular day. The variable of interest in Equation (1) is θ, which measures the relation between noise trading and volatility. A positive θ indicates that noise traders increase the level of daily volatility, and vice versa.

Table II provides the regression results for the specification in Equation 1. As can be seen from the table, the average θ coefficients are positive for all volatility specifications. This indicates a *prima facie* positive relation between noise trading activity and daily volatility. A closer look at the significance levels confirms this observation. The θ coefficients are positive and significant in 73% of the cases at the 10% significance level, and 68% even at the 5% significance level. The results hence provide strong support for both Black's (1986) and DeLong's et al. (1990) predictions that noise trading will increase the level of volatility. The fact that noise traders are able to increase short term volatility above what can be explained rationally, means that this category of traders have a negative effect on market efficiency by reducing the price discovery process.

The regression results summarized in Table II appear to be well specified. The regression residuals show very little evidence of autocorrelation in the residuals as measures by the Ljung – Box portmanteau test for serial correlation in the squared residuals with 12 and 24 lags[3].

[Insert Table II here]

4.3 Noise Trading and Returns

Having established that noise traders increase the level of daily volatility, it is important to see whether noise traders also have a positive effect on daily returns. DeLong et al. (1990) and

[3] OLS regression results were also obtained, which incorporated alternate unconditional measures of volatility (daily squared returns, Parkinson's (1980) daily range, and Garman and Klass (1980) daily range). The results obtained from these OLS regressions are even stronger than for the GARCH specification. Results can be provided on request.

Campbell and Kyle (1993) predict that the additional risk that noise traders introduce into stock prices, is priced in the form of higher returns. We test the relation between noise trading activity and returns using the following specification:

$$r_t = \alpha + \beta NOISE_t + \sum_{i=1}^{4} \varphi_i r_{t-i} + \sum_{j=1}^{4} \gamma_i D_t + \sum_{k=1}^{11} \vartheta_j M_t + \theta VOL_{t-1} + \varepsilon_t, \qquad (2)$$

where the $\mathrm{r_t}$ is the daily return for day t, calculated as the log difference of closing and opening prices; $\mathrm{r_{t-i}}$ is the lagged return up to lag 4[4]; $\mathbf{D}$ is a day of the week dummy; $\mathbf{M}$ is a monthly dummy; $\mathrm{VOL_{t-1}}$ is the lagged trading volume. The variable of interest is β which reports the relation between noise trading and returns. A positive β indicates that noise traders increase daily returns, and vice versa. Table 3, presents the regression results from Equation (2).

Table III reports the average noise coefficient, together with the percentage of significant positive, and negative coefficients. The average noise coefficient is 0.16, which indicates that noise trading activity has a *prima facie* weak positive effect of daily stock price returns. However, only 16% (9%) of the regression coefficients are positive and significant at the 5% (1%) significance levels. Even at the 10% significance level, only for 24% of the stocks is the noise trading coefficient positive and significant. This indicates that contrary to the predictions of theoretical models, noise trading activity does not increase daily returns. The model appears to be well specified, not displaying any evidence of autocorrelation in the residuals - only in 6% of the cases the null hypothesis of no autocorrelation is rejected at the 5% significance level.

[Insert Table III here]

[4] The number of lags is chosen based on the BIC criteria.

The results obtained in this section indicate that noise trading activity does not affect the level of daily returns. This result is contrary to the predictions of theoretical models found in the literature. Coupled with the results obtained in the previous subsection, it can be concluded that noise traders introduce excess volatility into the market. This is because noise traders increase the level of stock price volatility, while at the same time not increasing the level of daily returns. These results indicate that noise traders have an undesirable effect on the market. Policy makers should introduce measures that will reduce the effect that noise traders have on stock price dynamics. The next subsection sheds some light on what factors underlying the stock, help reduce the impact that noise traders have.

4.4 Firm Size and Noise Trading

In this subsection, the relation of noise trading activity with daily volatility, and returns is tested across different firm size subsamples. Table IV provides noise coefficients obtained from the GARCH (1,1) model specification, after segregating according to firm size. The firms are classified according to market cap percentile. The top 25 percentile of the sample is classified as large cap firms, the bottom 25 percentile as small cap firms, and anything in between as medium sized firm.

Table IV shows that average noise coefficients are weakest for the large cap firms, slightly stronger for the medium cap stocks and strongest for the small cap firms. This is in line with the limits to arbitrage theory, as small firms have the most short sale restrictions, few derivative products, and lowest analyst following.

In addition, small firms also display lower percentages of positive and significant noise coefficients than corresponding large firms. This is despite the fact that small firms have a considerably higher average noise coefficient. A possible explanation of this paradox could lie in the visibility of stocks. Large cap stocks are more visible in the market than small cap stocks, and thus will be targeted to a larger extent by noise traders. However, because these visible firms can be expected to have low limits to arbitrage in the form of low short sale restrictions and high analyst following, this will translate into high number of arbitrageurs acting to offset the effect of noise traders. The resulting effect will be that although noise traders have some effect on more large cap stocks, their effect will be relatively weak. On the other hand given that small cap stocks are less visible, it can be expected that noise traders will ignore more of the small stocks altogether, thus having no effect on daily volatility. However, due to the limits to arbitrage, the stocks that noise traders do not ignore will be affected to a much larger extent than large or medium cap stocks.

[Insert Table IV here]

Table V reports the noise coefficient estimates measuring the relation between noise trading activity and daily returns from the OLS regression in Equation (2), after segregating according to firm size.

Consistent with the results presented in Table IV, the noise trading coefficients are considerably stronger for small cap stocks than medium or large cap firms. This can be seen from the substantially higher average noise coefficient and percentage of positive and significant coefficients. The average noise coefficient is highest for the small cap stocks together with the highest percentage of positive and significant coefficients. The medium cap stocks, which are defined as those between the top and the bottom 25 percentile have a significantly higher average noise coefficient than the large cap stocks. Most medium cap stocks classified by market cap percentile are outside the S&P/ASX 100 index. Therefore, it can be concluded that noise traders have the strongest positive effect on daily returns for firms outside the S&P/ASX 100 index.

[Insert Table V here]

The results obtained in Tables IV and V show that noise traders have an effect on the daily volatility and returns of stocks for all firm size subsamples, although this effect is greatest for the small cap firms. At the same time, the results also indicate that noise traders have a relatively weak effect on daily stock price returns – although the effect is strongest for firms outside the S&P/ASX 100 index. These results suggest, that contrary to the predictions of theoretical models such as DeLong et al. (1990) and Campbell and Kyle (1993), noise trader risk is not priced into stock price returns. The results further indicate that limits to arbitrage play an important role in market efficiency. Where such limits are the strongest, noise traders have the strongest effect on daily volatility, but nonetheless a weak effect on daily returns. The resulting conclusion that can be drawn is that measures attempting to reduce the negative effects that noise traders exert on the market should revolve around reducing the limits to arbitrage on smaller stocks.

4.5 Robustness Checks

Given that volatility is such a latent and unobservable concept, for robustness we used alternate measures of volatility. Specifically we incorporated the noise trading measure, together with the two liquidity control variables to the EGARCH and CGARCH equations. Also unconditional variance estimates were utilized, and the relation between noise trading and those measures was tested in an OLS framework. The results for these alternate models were very similar to those obtained in the GARCH model specification discussed in subsection 4.2. The regression results for the OLS model specification were even stronger than those reported in subsection 4.2. Furthermore, the relation between noise trading activity and returns was also tested by adding the noise trading measure to the mean equation of the GARCH model. Once again the results obtained were virtually identical to those reported in the previous section. Finally, we also tested the relation between noise trading activity with volatility and returns jointly in a GARCH (1,1) framework. This was done by adding the noise trading measure to both the mean equation and the variance equation. The benefit of performing such a joint test is that it shows the simultaneous effect that noise trading activity has on both volatility and returns. The results obtained from this joint test are in line with the results reported in the previous two subsections – noise trading activity has a positive effect on volatility and little effect on returns.

Alternate measures of noise trading, discussed in Section 3 were also incorporated to see whether the results are sensitive to alternate methodologies of accounting for differences in market share. For all alternate measures of noise trading, the results are virtually the same as those discussed in the previous two subsections[5].

5. Conclusion

The main objective of this paper was to examine empirically the theoretical prediction by Black (1986) and DeLong et al. (1990) that noise traders have a positive effect on daily volatility and that any additional risk which noise traders introduce is priced in the form of higher daily returns. Investigating a wide cross section of firms, listed on the ASX between 1st March 2006 and 29th February 2008, we provide empirical evidence of the correlation between noise traders' activities and price volatility using a direct proxy of noise trading. To best of our knowledge this is the first study to apply high frequency data and an efficient measure of noise trading while investigating the impact of the noise traders on market volatility and returns. Utilizing conditional and unconditional measures of volatility and returns, we find strong support for the notion that noise traders have a positive effect on volatility. However, we document weak

[5] Results discussed in this subsection are available on request.

evidence supporting the hypothesis that the additional risk in the form of increased stock price volatility is priced through increased daily returns. Our analysis shows that noise traders rarely have any statistically significant effect on stock price returns, and, when they do, the effect is relatively small.

We further examines within what subgroup of firms noise traders exert the strongest influence on stock prices. The results indicate that noise traders have a much stronger positive influence on the daily volatility of small cap firms compared with that of large cap stocks. Furthermore, noise traders also have a stronger positive effect on the daily returns of small firms compared with large stocks. However, their effect is considerably weaker on returns than on the volatility even for the smallest firms. We find that firms outside the S&P/ASX 100 index, which have considerably greater limits to arbitrage, are affected most by the activity of noise traders.

Our results provide strong support for the notion that noise traders have an undesirable effect on stock prices, and measures should be put in place to reduce this negative influence on market efficiency. By increasing daily volatility they introduce additional noisiness into stock prices and, therefore, distort the price discovery process, which is a pivotal characteristic of an efficient market. Shleifer and Summers (1990) note that higher transaction taxes should be introduced, which would discourage noise traders from excessive trading. Such suggestions however, ignore the fact that noise traders are suppliers of liquidity (Berkman and Koch, 2007), which is also an essential component of market efficiency. Bloomfield et al. (2008) show that transaction taxes are not an effective way of enhancing market efficiency. Furthermore, the distinction between noise traders and informed traders is ambiguous, since it is often difficult to separate with certainty what constitutes noisy information and what constitutes fundamental information.

The results in this study indicate that measures enhancing market efficiency do not need to focus on targeting noise traders as such. The problem rather lies with limits to arbitrage, which allow noise traders to have a negative effect on market efficiency. Rather than introducing transaction taxes which are likely to reduce market liquidity, we propose that policy makers ought to work on measures that will reduce the limits to arbitrage for the medium and small firms.

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Table I
Descriptive Statistics

This table provides descriptive statistics of daily data from 1st March 2006 through 29th February 2008, across 317 stocks on the ASX. All statistics are calculated across all stocks and days. There is an average of 480 daily observations for each stock in the sample. Panel A provides descriptive statistics for daily returns and liquidity measures across the sample stocks. Reported Maximum and Minimum values are the median maximum and minimum values across all firms in the sample. Daily returns are calculated as the log difference of stock closing and opening prices. The price is the average closing price for the sample stocks. The daily spread is based on the best quotes in the limit order book and is calculated as the average of the difference between the bid and ask quotes across all intraday observations, where a change in the best quotes in the book was reported. The trading volume and number of transactions are the total number of shares traded and the total number of transactions on a particular day, respectively. Panel B provides descriptive statistics for various measures of daily unconditional and conditional volatility across sample stocks: Daily Squared Returns, Daily Range, Garman and Klass (1980) Adjusted Daily Range, GARCH, EGARCH and CGARCH. The CGARCH model is estimated and the temporary and permanent components are reported. Panel C provides descriptive statistics of the four alternative measures of daily noise trading activity across the sample stocks. Measure 1 refers to a standardization scheme, whereby each broker's daily net initiated order flow for each firm is standardized by that broker's standard deviation in daily net initiated order flow for each firm over the sample period. Measure 2 refers to a standardization scheme, whereby each brokers daily net initiated order flow for each firm is standardized by that broker's standard deviation in daily net initiated order flow across all firms over the sample period. Grouped measures of noise trading refer to grouping the brokers that initiate on less than 30 separate days together, thus forming one bigger broker. Panel D provides descriptive statistics for returns, unconditional and conditional volatility measures, classified by firm size. Panel E provides descriptive statistics for noise trading and liquidity measures, classified by firm size. In Panel D and E, the percentile classification scheme is used. This classification scheme assumes that large cap firms are the firms that constitute the top 25 percentile by market cap. Small firms are regarded as those that constitute the bottom 25 percentile by market cap, with anything in between regarded as medium sized firms. The table also reports the Ljung – Box statistics for autocorrelation in returns and volatility. Q(12) and Q(24) is the average Ljung – Box statistic for the 12th and 24th order respectively. The Q(12) and Q(24) columns report the percentage of cases in which the null hypothesis of no-autocorrelation is rejected at the 5% significance level. The reported returns and volatility measures are multiplied by 100.

Panel A: Returns and Liquidity Measures

	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	Q(12)	Q(24)
Returns	-0.09	-0.07	0.42	-0.68	-0.10	9.35	26%	29%
Price ($)	7.15	7.01	152.50	0.03	0.02	2.60		
Spread (%)	0.02	0.02	0.04	0.01	1.59	11.89		
Trading Volume ('000)	1229	952	258,000	0.568	3.77	33.56		
Number of Transactions	507	428	25,796	4	2.18	14.17		

Panel B: Daily Volatility

	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	Q(12)	Q(24)
Daily Squared Returns	0.05	0.01	0.47	0.00	7.12	82.32	68%	79%
Daily Range	0.06	0.02	12.78	0.00	6.48	71.06	96%	96%
Garman - Klass Daily Range	0.06	0.02	17.71	0.00	6.65	74.31	96%	95%
GARCH	0.17	0.11	4.45	0.00	3.75	31.31	97%	97%
EGARCH	53.81	0.05	71160	0.00	5.99	74.92	94%	94%
CGARCH: Temporary	0.06	0.04	0.19	0.00	4.33	39.68	99%	98%
CGARCH: Permanent	0.06	0.05	0.08	0.00	3.01	25.58	98%	98%

Panel C: Noise Trading Measures

	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	Q(12)	Q(24)
Measure 1: All Brokers	0.83	0.70	677.53	0.01	2.43	18.53	89%	88%
Measure 2: All Brokers	0.36	0.29	27.23	0.00	4.07	35.74	87%	85%
Measure 1: Grouped Brokers	0.80	0.68	7.75	0.00	1.86	9.12	92%	91%
Measure 2: Grouped Brokers	0.36	0.28	27.06	0.00	4.15	36.69	89%	86%

Panel D: Returns and Volatility by Firm Size

	Large Cap Firms			Medium Cap Firms			Small Cap Firms		
	Median	**Maximum**	**Minimum**	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**	**Minimum**
Returns	-0.07	0.23	-0.68	-0.06	0.32	-0.35	-0.10	0.42	-0.68
Daily Sqaured Returns	0.01	0.46	0.00	0.01	0.13	0.00	0.02	0.47	0.00
Daily Range	0.01	12.78	0.00	0.02	0.21	0.00	0.03	0.17	0.00
Garman - Klass Adjusted Range	0.02	17.71	0.00	0.02	0.29	0.00	0.03	0.18	0.00
GARCH	0.02	0.14	0.00	0.18	4.45	0.00	0.07	0.10	0.00
EGARCH	0.02	0.52	0.00	0.04	0.28	0.00	0.08	0.79	0.00
CGARCH: Temporary	0.02	0.19	0.00	0.04	0.04	0.00	0.07	0.10	0.00
CGARCH: Permanent	0.02	0.06	0.00	0.04	0.05	0.00	0.08	0.08	0.00

Panel E: Noise Trading and Liquidity by Firm Size

	Large Cap Firms			Medium Cap Firms			Small Cap Firms		
	Median	**Maximum**	**Minimum**	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**	**Minimum**
Noise	0.77	24.86	0.02	0.73	6.32	0.04	0.67	677.53	0.01
Spread	0.02	0.03	0.01	0.01	0.04	0.01	0.02	0.05	0.01
Trading Volume ('000)	1,528	258,000	2	629	144,000	1	271	258,000	1
Number of Transactions	1,230	25,796	7	443	21,560	4	177	21,560	4

Table II
Noise Trading Activity and Volatility

This table presents results obtained when testing for the relation between noise trading activity and volatility for a sample of 317 stocks on the ASX, from 1st March 2006 to 29th February 2008. The results are obtained from estimating the following GARCH(1,1) model:

$$r_t = \mu + \varepsilon_t, \qquad \varepsilon_t | \Omega_{t-1} \sim \mathrm{i.i.d}(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \theta \mathrm{NOISE}_t + \varphi \mathrm{SPREAD}_{t-1} + \vartheta \mathrm{VOL}_{t-1}$$

where r_t is the stock price return for day t; NOISE_t is the measure of noise trading activity on day t; SPREAD_{t-1} is the previous day's average spread; VOL_{t-1} is the previous day's trading volume; ω is a constant term and σ_t^2 is the conditional variance of the error term process ε_t, which follows a student t-distribution. The results are obtained using the Marquardt iterative algorithm. Only the coefficient of interest is reported (θ), which measures the relation between noise trading activity and daily volatility. The reported coefficient is the average of θ across 317 stocks, multiplied by 1000. The percentage of significant positive and negative coefficients is reported at 1%, 5% and 10% significance levels respectively.

$Q^2(12)$ and $Q^2(24)$ is the Ljung – Box portmanteau test for serial correlation in the squared residuals with 12 and 24 lags respectively. The average coefficient is reported, together with the percentage of cases in which the null hypothesis of no serial correlation is rejected at the 1%, 5% and 10% significance levels respectively.

		α = 0.01		α = 0.05		α = 0.10	
	Coefficient	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
θ	0.21	57%	0%	68%	4%	73%	5%
$Q^2(12)$	13.53	9%		16%		19%	
$Q^2(24)$	27.15	12%		17%		22%	

Table III
Noise Trading Activity and Returns

This table presents results obtained when testing for the relation between noise trading activity and daily returns for a sample of 317 stocks on the ASX, from 1st March 2006 to 29th February 2008. The results are obtained from estimating the following OLS regression:

$$r_t = \alpha + \beta NOISE_t + \sum_{i=1}^{4} \varphi_i r_{t-i} + \sum_{j=1}^{4} \gamma_i D_t + \sum_{k=1}^{11} \vartheta_j M_t + \theta VOL_{t-1} + \varepsilon_t$$

where the r_t is the daily return for day t, calculated as the log difference of closing and opening prices; r_{t-i} is the lagged return up to lag 4; D is a day of the week dummy; M is a monthly dummy; VOL_{t-1} is the lagged trading volume. Only the coefficient of interest (β) is reported, together with the percentage of significant positive and negative coefficients. The reported coefficient is the average of β across 317 stocks, multiplied by 100.
Q^2(12) is the average Ljung – Box portmanteau test for serial correlation in the squared residuals with 12 lags. The table provides the percentage of cases in which the null hypothesis of no – serial correlation is rejected at the 1%, 5% and 10% significance levels, respectively. The regression Adjusted R^2 is also reported.

		α = 0.01		α = 0.05		α = 0.10	
	Coefficient	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
β	0.16	9%	3%	16%	5%	24%	7%
Q(12)	10.71	3%		6%		8%	
Adjusted R^2	6%						

Table IV
Noise Trading Activity and Volatility by Firm Size

This table presents the relation between noise trading activity and daily volatility, across three different firm size segments, for a sample of 317 stocks on the ASX, from 1st March 2006 to 29th February 2008. The results are based on the percentile classification scheme. The classification scheme assumes that large cap firms are the firms that constitute the top 25 percentile by market cap. Small firms are regarded as those that constitute the bottom 25 percentile by market cap, with anything in between regarded as medium sized firms. The regression results are based on the GARCH (1,1) conditional variance model results, reported in Table II. Only the average coefficient of interest multiplied by 1000 is reported (θ), together with the percentage of significant positive and negative coefficients at the 1%, 5% and 10% confidence interval.

		α = 0.01		α = 0.05		α = 0.10	
	Noise Coeff.	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
Large Firm	0.10	56%	0%	77%	0%	84%	1%
Medium Firms	0.19	54%	3%	63%	4%	67%	5%
Small Firms	0.37	64%	4%	69%	7%	73%	8%

Table V
Noise Trading Activity and Returns by Firm Size

This table presents the relation between noise trading activity and daily returns, across three different firm size segments, for a sample of 317 stocks on the ASX, from 1st March 2006 to 29th February 2008. The results are based on the percentile classification scheme. The classification scheme assumes that large cap firms are the firms that constitute the top 25 percentile by market cap. Small firms are regarded as those that constitute the bottom 25 percentile by market cap, with anything in between regarded as medium sized firms. The regression results are based on the OLS regression presented in Table III. Only the average coefficient of interest is reported θ, together with the percentage of significant positive and negative coefficients at the 1%, 5% and 10% confidence interval.

		α = 0.01		α = 0.05		α = 0.10	
	Noise Coeff.	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
Large Firm	0.81	4%	0%	12%	4%	16%	5%
Medium Firms	1.57	12%	3%	20%	6%	27%	9%
Small Firms	1.91	14%	1%	22%	5%	29%	5%