Deafened by Noise:
Do Noise Traders Affect Volatility and Returns?

Edward Podolski – Boczar[a], Petko S. Kalev[a]* and Huu Nhan Duong[b]

This draft: 29 May 2009

Abstract

This paper considers 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, we document 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 Classification: G12, G14
Keywords: Information; Noise trading; Limits to arbitrage; Market efficiency; Volatility

[a] Department of Accounting and Finance, Monash University, Australia
[b] School of Accounting, Economics and Finance, Deakin University

*Corresponding author: Petko S. Kalev, Department of Accounting and Finance, Faculty of Business and Economics, P.O. Box 197, Caulfield East, VIC 3145 Australia. Tel: +613 9903 2431 Fax: +613 9903 2422 Email: Petko.Kalev@BusEco.Monash.edu.au.

Acknowledgements: We thank Ron Balvers, Paul Lajbcygier, Edwin Maberley, Raylene Pierce-Maberley, Doug Foster, Pawel Podolski - Boczar and participants at the 21st Australasian Finance & Banking Conference Sydney 2008, the University of Sydney Microstructure Meeting 2009 and, the FMA Asian Conference for providing comments on the earlier draft of the paper. We are grateful to the Securities Industry Research Centre of Asia-Pacific (SIRCA) for providing the data used in this study. The usual caveats apply.

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 (De Long et al., 1990, Campbell and Kyle, 1993 and others). In addition, we examine whether noise traders increase returns. Consistent 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 (De Long 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 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; De Long et al., 1990; Andrade et al., 2008; 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 direct proxies of noise trading at daily frequencies based on both dispersion in net initiated order flows (Berkman and Koch, 2008) and number of small retail transactions (Barber et al., 2009).

Second, understanding what impact noise traders have on stock price volatility and returns has economic significance, as it allows investors to make more informed portfolio allocation decisions. Dumas et al. (2009) 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 (increased volatility not accompanied by greater return) 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. The general preconception based on largely anecdotal evidence is that noise traders contribute to excess volatility. Some authors (Summers and Summers, 1989; Shleifer and

[1] Baker and Stein (2004) and Berkman and Koch (2008) 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), amongst others find negative relation between liquidity and volatility.

Summers, 1990) have argued that policy makers should implement measures that reduce the level of noise trading in the market, 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 utilizing two daily proxies of noise trading based on intra-day information (Berkman and Koch, 2008, Barber et al., 2009). Studying the relation at daily intervals is important, as any effect which noise traders have on the market will be greatest 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).

Second, we test the prediction put forward by De Long et al. (1990) and Campbell and Kyle (1993) that noise traders have a positive effect on returns. This examination provides answers to the question of 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 De Long et al. (1990), noise traders have a positive effect on daily stock price volatility. Contrary to De Long 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. However, our CGARCH test results indicate that noise traders only affect short term volatility, without having any significant effect on the permanent component of volatility. This could explain why noise traders have no 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. Such measures would not only increase the trading activity of arbitrageurs amongst the small cap stocks, but would also have the potential to increase liquidity.

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.

There is a general consensus in the literature that retail investors are a prime candidate for being noise traders. Based on the 'stealth trading' hypothesis, Chakravarty (2001) documents that institutions are the informed traders, implying that retail traders are the uninformed traders. Kurov and Sancetta (2008), studying large and small trades in the futures market also conclude that retail traders are noise traders, while institutional investors are informed traders. Barber et al. (2009) argue that small retail investors are noise traders, due to their limited access to valuable information and expertise in applying any information they obtain. They use the number of small initiated transactions to proxy for noise trading activity. Nonetheless, 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

De Long 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; De Long 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, 2008; Bloomfield et al., 2009) and informational efficiency (Bloomfield et al., 2009; Kurov, 2008), the relation between noise trading and daily volatility has been relatively sparse. Koski et al. (2004) was one of the first to consider this question. Utilising 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 individuals 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

De Long 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 De Long 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 De Long et al. (1990) and Campbell and Kyle (1993). Investor sentiment has been used in the literature as a proxy of noise trading. 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 De Long 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 De Long 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 De Long'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

De Long et al. (1990) argue that the price of a stock is likely to diverge from fundamental value in the short to medium term in the presence of noise traders. This is because risk bearing noise traders who have the ability to move prices away from fundamental values will discourage risk averse arbitrageurs from actively trading. Similar arguments against the efficiency of arbitrageurs in ensuring prices reflect fundamental values have been put forward by other authors (see, among others, Shleifer and Summers, 1990; and Shleifer and Vishny, 1997).

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, 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 and Sorescu (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 including the transaction 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 (2008). Furthermore, brokers are identified, based on their identities, as retail brokers, institutional brokers or brokers that provide services to both institutional and retrial investors.[3] 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 is treated as a 'trading day' if there are at least four distinct brokers who initiate trades during that trading session (Berkman and Koch, 2008). In line with Berkman and Koch (2008), 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 303 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 ask 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 the best bid and ask quotes across all intraday observations, where a change in the best quotes in the book was reported. The daily

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

[3] This classification is based on brokers' identity, as provided by IRESS. For a more detailed discussion of this classification, see Duong et al. (2009).

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

Two measures of noise trading are utilised in the current study, based on prior literature. The first measure is based directly on that proposed by Berkman and Koch (2008). The idea behind the proxy is that informed traders will mimic the market when initiating trades such as to camouflage their transactions. Therefore, their trading activity will be undistinguishable from uninformed noise traders. More specifically, informed traders will fragment their trades across brokers based on each broker's market share and the dispersion in net initiated order flows (NIOF) across brokers. The net effect of this behaviour will be that trading activity by informed traders will not affect the daily dispersion in NIOF, and in turn any dispersion in daily NIOF will be attributed only to noise traders. Greater dispersion in NIOF across brokers through which noise traders after all trade indicates greater noise trading activity on a given day for a given stock. NIOF is defined as the number of buy initiated transactions less the number of sell initiated transactions for each stock.

For the purpose of calculating the proxy of noise trading, we first standardise each brokers daily NIOF by that broker's standard deviation in daily NIOF's over the sample period. It is assumed that brokers with greater market share will have a higher standard deviation in NIOF's over the sample period compared with smaller brokers. After standardising each broker for market share, we then calculate the daily dispersion in standardised NIOF's across brokers for a particular stock. This dispersion measures the level of daily noise trading activity for each stock in our sample.

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[4]. These grouped brokers are treated as one large broker. The average number of small brokers in our sample is 4.

A potential problem with the Berkman and Koch (2008) proxy is that it might not be capturing only noise trading activity, if informed traders do not behave the way it is assumed that they behave. More specifically, if informed traders initiate transactions through a select group of preferred brokers rather than according to that day's dispersion in NIOF, the proxy will not necessarily be reflecting true noise trading activity. For this reason we use an alternate proxy of daily noise trading, proposed by Barber et al. (2009). The proxy is based on the assumption, that noise traders are predominantly small individual investors, who do not have the knowledge nor resources to trade in an informed way. The level of daily noise trading activity for a given stock is measured by the number of small trades made by retail traders. The definition of a small trade differs across different market capitalisations. For the large cap sample (top percentile by market cap), trades where the volume is below 300 is classified in this group. For medium cap stocks, trades where the volume is below 600 are classified as small trades. Finally, for small cap stock, trades where the volume is below 1300 are regarded as small retail transactions. This choice of cut off levels is based on the average bottom quartile size of retail transaction across stocks in the different market cap categories.

[4] The choice of 30 is arbitrary; however the results are robust to other grouping criteria such as 10, 20, 40, or 50.

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 to be expected 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 large variability in return and liquidity measures reported in Panel A, of Table I, is indicative of the fact that a 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.

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 our conditional measure tends 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 both measures of noise are non – normally distributed. All measures of noise have kurtosis considerably greater than 3, indicating that they have fatter tails compared with a normal distribution. Furthermore, all measures of noise are positively skewed.

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 cap firm subsample however, displays the most negative average daily returns. This once more is justifiable, given that after the subprime mortgage crisis emerged, small firms regarded as the riskiest would have been dumped first. 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. The volatility tends to be lowest for large cap stocks. This is in line with Berkman and Koch (2008), who find that price sensitivity is greatest for less liquid stocks, which can be expected to be the smaller market cap 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

We first proceed to examine the relation between noise trading activity and daily volatility by estimating a simple OLS regression in the following form:

$$\sigma_t^2 = \alpha + \theta \mathrm{NOISE}_t + \varphi \mathrm{SPREAD}_{t-1} + \vartheta \mathrm{VOL}_{t-1} + \varepsilon_t \quad (1)$$

In Equation (1), σ_t^2 refers to an unconditional measure of volatility such as daily squared returns, daily range or Garman-Klass adjusted daily range. NOISE_t is the measure of noise trading on day t; SPREAD_{t-1} is the previous days bid – ask spread; and $\mathrm{VOL}_{t-1}$is the previous day's trading volume. Daily spread is calculated as the average of the difference in bid and ask quotes 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 shares 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, Panel A provides the average θ coefficients for the regression formulated in Equation (1). Results are provided for both the Berkman and Koch (2008) (proxy 1) and Barber et al. (2009) (proxy 2) measures of noise trading. It can be seen from the panel that the θ coefficients are positive and significant in the majority of firm specific regressions for all measures of volatility. The results are the strongest for the daily range based measures of volatility and weakest for the daily squared returns measure. Noise trading activity appears to be able to explain more of the variation in volatility based on daily range type measures, as it is evident by a considerably highR^2. This result is to be expected given the general inefficiency attributed to daily squared returns as a measure of volatility (Martins and van Dijk, 2006).

Given the evidence of kurtosis in returns reported in the previous subsection, the GARCH(1,1) methodology has also 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:

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

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

In Equation (2), 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 $\mathrm{VOL}_{t-1}$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.

Table II, Panel B provides the regression results for the specification in Equation (2). As can be seen from the table, the average θ coefficients are positive. This indicates a *prima facie* positive relation between noise trading activity and daily volatility, which is confirmed by a closer look at the significance levels. The θ coefficients for regressions obtained using proxy 1 (proxy2) are positive and significant in 73% (70%) of the cases at the 10% significance level, and 68% (63%) even at the 5% significance level. The results hence provide strong support for both Black's (1986) and De Long'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, Panel B 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[5]. Furthermore, the results are robust across the two alternate proxies of noise trading.

[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. De Long et al. (1990) and 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:

$$r_t = \alpha + \beta NOISE_t + \sum_{i=1}^{4} \varphi_i r_{t-i} + \sum_{j=1}^{4} \gamma_i D_t + \sum_{k=1}^{11} \vartheta_j M_t + \theta VOL_{t-1} + \varepsilon_t \qquad (3)$$

In Equation (3) $\mathrm{r_t}$ 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 four [6] D is a day of the week dummy; 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 III, presents the regression results from Equation (3).

---

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

Table III reports the average noise coefficient, together with the percentage of significant positive and negative coefficients. For regressions using proxy 1, the average noise coefficient is 0.16 indicating that noise trading activity has a *prima facie* weak positive effect of daily stock price returns. However, only 24% (16%) of the regression coefficients are positive and significant at the 10% (5%) significance levels. This indicates that contrary to the predictions of theoretical models, noise trading activity does not increase daily returns.

However, results where we use proxy 2 are somewhat different. The average noise trading coefficient is negative (-0.03), with the majority of significant coefficients being negative (21% (27%) negative to 4% (5%) positive at the 5% (10%) significance level). This is a significant difference, as the results obtained using proxy 2 indicate that noise traders not only make prices more noisy in the short term (by making them more volatile), but also reduce short term returns. Despite this considerable difference, for both measures it is found that noise traders have a statistically weak effect on returns.

[Insert Table III here]

The results obtained in this section indicate that noise trading activity does not strongly affect the level of daily returns (β significant in only 30% of the cases for both proxies). This result is contrary to the predictions of theoretical models. 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 a possible reason why noise traders have little effect on returns.

4.4 Temporary and Permanent Components of Volatility

The results obtained in the previous two subsection call for further evaluation. In the spirit of De Long et al. (1990) it is expected that noise traders should affect both volatility and returns. The weak relation observed between noise trading and daily returns could however, be explained by the fact that noise traders only affect the temporary component of volatility and not the permanent component. If this were the case than one would not expect noise traders to be able to have a significant ability to impact returns.

We test the effect of noise traders on the two component of volatility by incorporating the CGARCH-in-mean model. The relation with the temporary component is measured using the following specification:

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

$$\sigma_t^2 - m_t = \alpha(\epsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) + \theta NOISE_t + \varphi SPREAD_{t-1} + \vartheta VOL_{t-1}, \quad (4)$$

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; m_t is the mean reverting level of volatility and σ_t^2 is the conditional variance of the error term process ε_t, which follows a student t-distribution.

Regression results specified in Equation (4) are reported in Table IV, Panel A. The relation between noise trading activity and the temporary component of volatility is rather strong, with 54% (64%) of the coefficients being positive and significant for proxy 1 and 60% (66%) for proxy 2 at the 5% (10%) significance level. The relation with returns remains weak however, with only 23% (31%) significant coefficients for proxy 1 and 17% (23%) for proxy 2 at the 5% (10%) significance level.

We proceed to test the relation with the permanent component of volatility with the following specification:

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

$$m_t = \omega + \rho(m_{t-1} - \omega) + \gamma(\varepsilon_{t-1} - \sigma_{t-1}^2) + \theta NOISE_t + \varphi SPREAD_{t-1} + \vartheta VOL_{t-1} \quad (5)$$

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; m_t is the mean reverting permanent component of volatility and σ_t^2 is the conditional variance.

The results are reported in Table IV, Panel B. Distinct from the temporary component, the results for the permanent component are rather weak. Noise traders are found to have a positive effect on the long run component of volatility in only 27% (30%) of the cases using proxy 1, and 30% (39%) of the cases using proxy 2 at the 5% (10%) significance level. The relation with returns remains weak. The average λ coefficient is weaker compared with the temporary component equation (0.21 for temporary component and 0.19 for permanent component). This result is consistent with the results showing that noise traders only have a strong effect on the temporary component of volatility.

[Insert Table IV here]

4.5 Firm Size and Noise Trading

In this subsection, the relation between noise trading activity and daily volatility, and returns is tested across different firm size subsamples. Table V provides noise coefficients obtained from the CGARCH–in -mean 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.

It can be seen from Table V, Panel A 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. The trends are the same for the two proxies of noise trading used. 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. Furthermore, the factors limiting arbitrage also play a role in reducing liquidity. The lower levels of liquidity within the small cap sample make prices more sensitive and therefore enable noise traders to affect prices to a larger extent. This observation is confirmed by the percentage of positive (negative) and significant coefficients. The portion of firms being affected by noise trading activity steadily increases as the firm size decreases.

Panel B shows the relation between noise trading and the permanent component of volatility. Similarly as for the temporary component, the average noise trading coefficient is the strongest for the small cap sample and the weakest for the large cap sample. This is an interesting observation, which is in line with the limits to arbitrage theory. Arbitrageurs are able to bring prices back to fundamentals only in the longer term. Given that large and medium stocks have considerably fewer limits to arbitrage, noise traders will have a smaller impact on the permanent component of volatility of those stocks. Small stocks on the other hand, with considerably greater limits to arbitrage, will be affected to a much larger extent.

[Insert Table V here]

Table VI reports the noise coefficient estimates measuring the relation between noise trading activity and daily returns from the CGARCH – in – mean equation. The results are in line with the volatility results reported in Table V. Once again, for both proxies we observe that the relation between noise trading activity and returns is strongest for the small cap stocks, and weakest for the large cap stocks. This trend is consistent across the two proxies of noise trading, and both the permanent and temporary component CGARCH – in – mean equations. Given that we observed that noise traders have a greater ability to influence the permanent component of volatility for the small cap sample compared with the large cap sample, the stronger relation with returns for that sub-group is not surprising.

[Insert Table VI here]

4.6. Discussion of Results

Contrary to expectations of theoretical models stemming from the work of De Long et al. (1990), our study indicates that any additional risk that noise traders introduce into the market is not priced in the form of higher returns. This result is however, most likely attributed to the fact that noise traders have only a minor effect on long run component of volatility. The small sample of stocks whose permanent component of volatility is affected to a larger extent, also display a stronger relation with daily returns.

Our results do however support the notion that noise traders through their trading activity make prices more volatile. This finding is contrary to prior work of Verma and Verma (2007) and Kurov (2008) who find that noise traders have a negative effect on volatility. A possible reason explaining the contradictory results could lie in the fact that both Verma and Verma (2007) and Kurov (2008) examined the relation over longer periods of time, whereas we looked at daily intervals. It is possible that over short horizons, noise traders make prices more volatile due to acting on non-fundamental noisy information, however in the medium term they will reduce market volatility through being suppliers of liquidity.

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, 2008), which is also an essential component of market efficiency. Bloomfield et al. (2009) 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 our study indicate that measures enhancing market efficiency do not need to focus on targeting noise traders as has been suggested. 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. Such measures will encourage arbitrageurs to take an active role in reverting prices back to fundamentals for this subgroup of stocks, and will enhance market efficiency.

4.7 Robustness Checks

The Berkman and Koch (2008) measure of noise trading utilised in this study is based on some underlying assumptions as to how informed investors behave. The proxy assumes that if informed investors initiate transactions in line with that day's dispersion in NIOFs across brokers, they will not have any effect on the dispersion. Any dispersion in NIOF will therefore be due to the trading activity of noise traders. Given that it is impossible to specify with certainty how informed investors exactly behave, for robustness we adjust the Berkman and Koch (2008) for the assumption made by Barber et al. (2009) that noise traders are predominantly retail traders. The final measure of noise trading is therefore effectively a combination of the two previous proxies. We proceed to calculate daily noise trading activity by once again measuring the dispersion in NIOF across brokers for a particular stock. However, we only look at the transactions initiated by retail brokers.

Test results based on the alternative measure of noise trading are presented in this section. Statistical models are exactly the same as those formulated in subsection 4.2 and 4.3. Table VII, Panel A reports the results of the relation between noise trading activity and unconditional volatility measures. It can be seen from the table that results are consistent with those obtained using the Berkman and Koch (2008) measure of noise trading. With the exception of daily squared returns, the noise trading coefficients are positive and significant in the majority of firms at the 5% significance level. At the 10% significance level noise coefficients are positive and significant in the majority of firms for all volatility measures.

Panel B shows the test results of the GARCH (1,1) model. As with unconditional measures, the results are consistent with those provided in subsection 4.2. Once again the noise trading coefficient is positive and significant in the majority of cases at both the 5% and 10% significance levels.

Consistent with the results obtained in subsection 4.3, our results also show that regardless of what measure of noise trading is used no relation is found to exist with daily returns. Panel C shows the test results for Hypothesis 2. It can be seen from the table that noise trading activity has any positive and significant effect on daily returns in only 11% of the cases at the 5% significance level.

[Insert Table VII here]

In order to see whether there is any endogeneity issue with the results obtained in this study, we incorporate the Durbin-Wu-Hausman test (for more details see Davidson & MacKinnon, 1993). The test results indicate that there is no endogeneity problem in our regression. More specifically, the results allow us to conclude that noise trading is causing an increase in volatility, and not the other way.[7]

Finally, alternate NIOF standardisation schemes are incorporated in the study. Standard deviation in broker daily NIOF over the sample period was calculated alternatively across one stock and across all stocks. Also, for the purpose of standardisation, we grouped 10, 20, 30, 40 and 50 smallest brokers together respectively. For all alternate standardisation schemes the results were virtually the same as those discussed in the previous two subsections.[8]

5. Conclusion

The main objective of this paper is to examine empirically the theoretical prediction by Black (1986) and De Long et al. (1990). Those theoretical models predict 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 direct proxies of noise

[7] Granger causality tests further confirm this finding

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

trading. 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 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. This observation is explained by the fact that noise traders only affect the temporary component of volatility rather than the permanent component.

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 do find however, that small stocks, whose permanent component of volatility is affected to a larger extent by the trading activity of noise traders, have a stronger relation with daily returns compared with other subsamples.

Our results indicate that measures revolving around reducing limits to arbitrage would be the most efficient in reducing the negative effect that noise traders have on the market. This is because noise traders seem to have the greatest negative effect on small cap stocks which have the strongest limits to arbitrage and lowest liquidity.

References

Admati, A.R., Pfleiderer, P., 1988. A theory of intraday patterns: volume and price variability. *Review of Financial Studies,* 1, 3 – 40.

Andrade, S., Chang, C., Seasholes, M., 2008. Trading imbalances, predictable reversals, and cross - stock price pressure. *Journal of Financial Economics*, 88, 406 – 423.

Baker, M., Stein, J., 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 7, 271 – 299.

Barber, B.M., Odean, T., Zhu, N., 2009. Do retail trades move markets?. *Review of Financial Studies* 22, 151 – 186.

Berkman, K., Koch, P., 2008. Noise trading and price formation process. *Journal of Empirical Finance*, 15, 232 – 250.

Black, F., 1986. Noise. *The Journal of Finance*, 51, 529 – 543.

Bloomfield, R., O'Hara, M., Saar, G., 2009. How noise trading affects markets: An experimental analysis. *Review of Financial Studies*, (forthcoming).

Boehme, R.D., Sorescu. S.M., 2002. The long-run performance following dividend initiations and resumptions: Underreaction or product of chance? *Journal of Finance,* 57(2), 871 – 900.

Bollerslev, T., Chou, R., 1992. ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics*, 52(1), 5 – 59.

Brown, G., Cliff, M., 2005. Investor sentiment and asset valuation. *Journal of Business*, 78, 405 – 438.

Campbell, J., Kyle, A., 1993. Smart money, noise trading and stock price behavior. *Review of Economic Studies*, 60, 1 – 34.

Chakravarty, S., 2001. Stealth trading: Which traders' trades move stock prices?. *Journal of Financial Economics*, 61, 289 – 307.

Copeland, T., Galai, D., 1983. Informational effects on the bid ask spread. *Journal of Finance*, 38, 1457 – 1469.

Cornell, B., Liu, Q., 2001. The parent company puzzle: When the whole is worth less than one of the parts? *Journal of Corporate Finance*, 7, 341 - 366.

Danthine, J., Moresi, S., 1993. Volatility, information, and noise trading. *European Economic Review*, 37, 961 – 982.

Davidson, R. and MacKinnon, J.G. 1993. Estimation and Inference in Econometrics, Oxford University Press: New York.

De Long, J.B., Shleifer, A., Summers, L., Waldmann, R., 1990. Noise trader risk in financial markets. *Journal of Political Economy*, 98, 703 – 738.

Dumas, B., Kurshev., Uppal , R., 2009. Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility. *Journal of Finance,* 64(2), 579 - 629.

Duong, H.N., Kalev, P., Krishnamurti, C., 2009. Order aggressiveness of institutional and individual investors. *Pacific-Basin Finance Journal, forthcoming.*

Foster, F.D., Viswanathan, S., 1990. A theory of interday variations in volume, variance and trading costs in securities markets, *Review of Financial Studies*, 4, 595-624

Foucault, T., Sraer, D., Thesmar, D., 2008. Individual investors and volatility. *Working paper*, HEC, School of Management.

Garman, M., Klass, M., 1980. On the estimation of security price volatilities from historical data. *Journal of Business*, 53, 67 – 78.

Handa, P., Schwartz, R., 1996. Limit order trading. *Journal of Finance*, 51(5), 1835 – 1862.

Hong, H., Lim, T., Stein, J., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55, 265 – 295.

Jones, C., Lamont, O., 2002. Short sales constraints and stock returns. *Journal of Financial Economics*, 66, 207–239.

Kelly, M., 1997. Constrains beware. *Forbes*, 159, 194.

Koski, J., Rice, E., Tarhouni, A., 2004. Noise trading and volatility: Evidence from day trading and message boards. *Working Paper*. University of Washington - Michael G. Foster School of Business.

Kurov, A., 2008. Investor sentiment, trading behavior and informational efficiency in index futures markets. *The Financial Review*, 43, 107 – 127.

Kurov, A., Sancetta, A., 2008. Who makes noise? Evidence from the e-mini index futures markets. *Journal of Financial Research,* 31, 247 – 270.

Lamont, O., Thaler, R., 2003. Can the market add and subtract? Mispricing in tech stock carve-outs. *Journal of Political Economy,* 111, 227 - 268.

Lee, C.M.C., Shleifer, A., Thaler, R.D., 1991. Investor sentiment and the closed - end fund puzzle. *Journal of Finance*, 46, 75 – 109.

Lee, W., Jiang, C., Indro, D., 2002. Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking and Finance*, 26, 2277 – 2299.

Martens, M., van Dijk, D., 2006. Measuring volatility with realized range. *Journal of Econometrics.* 138, 181 – 207.

Mitchell, M., Pulvino, T., Stafford, E., 2002. Limited arbitrage in equity markets. *Journal of Finance*, 57, 551–584.

Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 53, 61 – 65.

Schill, M., Zhou, C., 2001. Pricing an emerging industry: Evidence from internet subsidiary carve-outs. *Financial Management*, 3, 5-33.

Shiller, R. J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends?. *American Economic Review*, 71, 421–36.

Shleifer, A., Summers, L., 1990. The noise trader approach to finance. *Journal of Economic Perspectives*, 4, 19 – 33.

Shleifer, A., Vishny, R., 1997. The limits of arbitrage. *Journal of Finance*, 52, 35 – 55.

Summers, L., Summers., 1989. When financial markets work too well: A cautious case for a scenario transaction tax. *Journal of Financial Services Research*, 3, 261 – 286.

Verma, R., Verma, P., 2007. Noise trading and stock market volatility. *Journal of Multinational Financial Management*, 17, 231 – 243.

Table I
Descriptive Statistics

This table provides descriptive statistics of daily data from 1st March 2006 through 29th February 2008, across a sample of 303 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 daily spread 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, and GARCH(1,1). Panel C provides descriptive statistics of the two alternative measures of daily noise trading activity across the sample stocks. The Berkmand and Koch (2008) measure is based on the dispersion in NIOFs across all brokers on a given day for a given stock. The Barber, Odean and Zhu (2009) proxy measures the number of small retail transactions for a given stock on a given day. 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 reported returns and volatility measures are multiplied by 100.

Panel A: Returns and Liquidity Measures

	Mean	Median	Maximum	Minimum	Skewness	Kurtosis
Returns	-0.09	-0.07	0.42	-0.68	-0.10	9.35
Spread	0.02	0.02	0.04	0.01	1.59	11.89
Trading Volume ('000)	1,229	952	4,790	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
Daily Squared Returns	0.05	0.01	0.47	0.00	7.12	82.32
Daily Range	0.06	0.02	0.90	0.00	6.48	71.06
Garman - Klass Daily Range	0.06	0.02	0.96	0.00	6.65	74.31
GARCH(1,1)	0.17	0.11	0.23	0.00	3.75	31.31

Panel C: Noise Trading Measures

	Mean	Median	Maximum	Minimum	Skewness	Kurtosis
Berkman and Koch (2008) proxy	0.80	0.68	7.75	0.01	1.86	9.12
Barber, Odean and Zhu (2009) proxy	30.94	22.25	253	1	1.45	5.45

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 Squared Returns	0.01	0.46	0.00	0.01	0.13	0.00	0.02	0.47	0.00
Daily Range	0.01	0.90	0.00	0.02	0.21	0.00	0.03	0.17	0.00
Garman-Klass Adjusted Range	0.02	0.96	0.00	0.02	0.29	0.00	0.03	0.18	0.00
GARCH(1,1)	0.02	0.14	0.00	0.21	0.23	0.00	0.07	0.10	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: Measure 1	0.78	3.20	0.17	0.68	3.67	0.09	0.65	3.79	0.01
Noise: Measure 2	77	253	9	23	170	1	10	84	1
Spread	0.02	0.03	0.01	0.01	0.04	0.01	0.02	0.05	0.01
Trading Volume ('000)	1,528	4,790	2	629	6,350	1	271	2.567	1
Number of Transactions	1,230	25,796	7	443	21,560	4	177	19,654	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 303 stocks on the ASX, over the sample period. Panel A provides results for unconditional measures of volatility. The panel provides the average coefficients across the sample stocks, as well as the percentage of significant positive and negative coefficients. Panel B provides the results for GARCH(1,1) measure of volatility. The panel provides the average coefficients across the sample stocks, as well as the percentage of significant positive and negative coefficients. $Q^2(12)$ 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 5% and 10% significance levels respectively. R^2 is the average of the Adjusted R-square. $\alpha = 0.05$ and $\alpha = 0.10$ refer to the 5% and 10% significance level, respectively. For both panels, results are provided for both the Berkman and Koch (2008) and Barber, Odean and Zhu (2009) measures of noise trading activity.

Panel A: Unconditional Volatility Relation with Noise Trading

	Berkman and Koch (2008)						Barber, Odean and Zhu (2009)					
		$\alpha = 0.05$		$\alpha = 0.10$				$\alpha = 0.05$		$\alpha = 0.10$		
	Coefficient	Positive	Negative	Positive	Negative	R^2	Coefficient	Positive	Negative	Positive	Negative	R^2
Daily Squared Returns	0.52	64%	0%	73%	0%	7%	0.0209	81%	0%	85%	0%	8%
Daily Range	0.70	79%	0%	85%	1%	18%	0.0204	92%	0%	93%	0%	18%
Garman - Klass Range	0.77	79%	0%	83%	1%	18%	0.0202	91%	0%	93%	0%	18%

Panel B: Conditional Volatility Relation with Noise Trading

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		$\alpha = 0.05$		$\alpha = 0.10$			$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
θ	0.21	68%	2%	73%	2%	0.01	63%	4%	70%	5%
$Q^2(12)$	12.21	9%		11%		13.53	16%		19%	
$Q^2(24)$	25.43	16%		20%		27.15	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 303 stocks on the ASX, over the sample period. Results are provided for both the Berkman and Koch (2008) and Barber, Odean and Zhu (2009) measures of noise trading activity. Average noise coefficient is provided across the sample stocks, as well as the percentage of significant positive and negative coefficients. The average coefficient is reported, together with the percentage of cases in which the null hypothesis of no serial correlation is rejected at the 5% and 10% significance levels respectively. Adjusted R^2 is the average of the Adjusted R-square. $\alpha = 0.05$ and $\alpha = 0.10$ refer to the 5% and 10% significance level, respectively.

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		$\alpha = 0.05$		$\alpha = 0.10$			$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
β	0.16	16%	5%	24%	7%	-0.03	4%	27%	5%	27%
Adjusted R^2	6%					7%				

Table IV
CGARCH–in –mean Results

This table presents results obtained when testing for the relation between noise trading activity and daily returns for a sample of 303 stocks on the ASX, over the sample period. Panel A provides results testing the relation between noise trading activity and the temporary component of volatility. The noise coefficient from the mean equation is also provided. Panel B provides results testing the relation between noise trading activity and the permanent component of volatility. The noise coefficient from the mean equation is also provided. The results are obtained using the Marquardt iterative algorithm. Only the coefficients of interest are reported (θ and λ). θ is the average noise trading coefficient from the variance equation multiplied by 1000, while λ is the average noise trading coefficient from the mean equation multiplied by 100. The reported coefficient is the average of θ (λ) across 303 stocks, multiplied by 1000 (100). The percentage of significant positive and negative coefficients is reported at 5% and 10% significance levels respectively. $Q^2(12)$ is the Ljung – Box portmanteau test for serial correlation in the squared residuals with 12 lags. The average coefficient is reported, together with the percentage of cases in which the null hypothesis of no serial correlation is rejected at the 5% and 10% significance levels respectively.

Panel A: Temporary Component of Volatility Test Results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		$\alpha = 0.05$		$\alpha = 0.10$			$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
θ	0.20	54%	0%	64%	0%	0.01	60%	0%	66%	1%
λ	0.21	19%	4%	26%	5%	-0.01	6%	11%	8%	15%
$Q^2(12)$	10.36	6%		8%		9.56	6%		8%	

Panel B: Permanent Component of Volatility Test Results

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		$\alpha = 0.05$		$\alpha = 0.10$			$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
θ	0.11	27%	1%	30%	1%	0.01	30%	1%	39%	1%
λ	0.19	20%	4%	27%	5%	-0.01	5%	13%	8%	19%
$Q^2(12)$	12.43	11%		15%		10.28	9%		12%	

Table V
Noise Trading Activity relation with Volatility and Firm Size

This table presents the relation between noise trading activity and daily volatility, across three different firm size segments, for a sample of 303 stocks on the ASX, over the sample period. 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 CGARCH-in-mean conditional variance model results, reported in Table IV. Only the average coefficient of interest multiplied by 1000 is reported (θ), together with the percentage of significant positive and negative coefficients at the 5% and 10% level of significance.

Panel A: Temporary Component of Volatility by Firm Size

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
Large Firm	0.10	47%	0%	60%	0%	0.001	53%	0%	59%	2%
Medium Firms	0.16	49%	0%	57%	0%	0.004	58%	1%	64%	1%
Small Firms	0.39	58%	0%	66%	1%	0.022	61%	0%	70%	0%

Panel B: Permanent Component of Volatility by Firm Size

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
Large Firm	0.05	23%	0%	26%	1%	0.001	27%	1%	35%	1%
Medium Firms	0.10	27%	2%	30%	2%	0.002	38%	1%	45%	1%
Small Firms	0.19	39%	0%	49%	0%	0.008	31%	0%	41%	0%

Table VI
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 303 stocks on the ASX, over the sample period. 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 CGARCH-in-mean conditional variance model results, reported in Table IV. Only the average coefficient of interest multiplied by 100 is reported (λ), together with the percentage of significant positive and negative coefficients at the 5% and 10% level of significance.

Panel A: Returns from Temporary Component Mean Equation by Firm Size

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
Large Firm	0.10	12%	6%	16%	8%	-0.009	5%	12%	6%	13%
Medium Firms	0.22	20%	3%	28%	3%	-0.023	6%	11%	9%	18%
Small Firms	0.31	23%	3%	34%	4%	0.081	8%	9%	10%	11%

Panel B: Returns from Permanent Component Mean Equation by Firm Size

	Berkman and Koch (2008)					Barber, Odean and Zhu (2009)				
		α = 0.05		α = 0.10			α = 0.05		α = 0.10	
	Coefficient	Positive	Negative	Positive	Negative	Coefficient	Positive	Negative	Positive	Negative
Large Firm	0.11	11%	4%	15%	7%	-0.001	2%	13%	3%	20%
Medium Firms	0.20	24%	3%	29%	4%	-0.001	4%	15%	9%	24%
Small Firms	0.28	21%	4%	33%	6%	-0.001	10%	11%	12%	11%

Table VII

Combined Proxy of Noise Trading Activity Results

This table presents results obtained when testing for the relation between noise trading activity and volatility and returns for a sample of 303 stocks on the ASX, from 1st March 2006 to 29th February 2008. Panel A provides results for the relation between noise trading activity and unconditional volatility. Panel B provides results for the relation between noise trading activity and GARCH(1,1) volatility. Panel C provides results for the relation between noise trading and returns.

Panel A: Noise Trading Relation with Unconditional Volatility

		$\alpha = 0.05$		$\alpha = 0.10$		
	Coefficient	Positive	Negative	Positive	Negative	R^2
Daily Squared Returns	0.46	42%	1%	55%	1%	7%
Daily Range	0.64	55%	1%	68%	1%	17%
Garman - Klass Range	0.72	53%	1%	63%	1%	17%

Panel B: Noise Trading Relation with GARCH(1,1) Volatility

		$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative
Θ	0.07	58%	4%	63%	4%
$Q^2(12)$	14.05	10%		19%	
$Q^2(24)$	27.30	14%		22%	

Panel C: Noise Trading Relation with Returns

		$\alpha = 0.05$		$\alpha = 0.10$	
	Coefficient	Positive	Negative	Positive	Negative
B	0.13	11%	2%	17%	4%
Q(12)	10.65	7%		9%	
Adjusted R^2	7%				