Information asymmetry and the bid-ask spread: Evidence from the UK

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Abstract

The generally accepted factors that determine the bid-ask spread are volatility, trading volume and market value (Atkins and Dyl, 1997, Glosten and Harris, 1988, and Menyah and Paudyal, 2000).

Using the framework developed in Kim and Verrecchia (1994), we suggest that the modelling of the spread should include the disagreement amongst market analysts concerning the firms' earnings. This variable captures the informational disadvantage of market makers with respect to informed traders. Market makers respond to the additional risk by increasing the bid-ask spread.

We find that the disagreement amongst analysts is significant, and with the hypothesised sign, in explaining FTSE 100 company spreads, rendering strong empirical support for the hypothesis proposed. The influence of the variability of analysts' forecasts is significant for horizons up to and including 6 months.

JEL Classification: C21, G10

Keywords: Spread, analysts' forecasts, trading volume, volatility of returns.

1. Introduction

One of the most important characteristics that investors look for in an organized financial market is liquidity. Liquidity is the ability to buy or sell significant quantities of a security quickly, anonymously, and with relatively little price impact. To maintain liquidity, many organized exchanges use market makers, who are individuals who are willing to provide a financial market whenever the investors want to trade. In return for providing liquidity, market makers are granted monopoly rights by the exchange to post different prices for purchases and sales. They buy at the bid price, P_b and sell at a higher ask price P_a. This ability to buy low and sell high is the market makers' primary source of compensation for providing liquidity. Their compensation is defined as $P_a - P_b$, which is defined as the bid-ask spread.

The quoted spread covers the costs of order processing, holding the inventory and adverse information costs. Studies such as Atkins and Dyl (1997), Constantinindes (1986), Glosten and Harris (1988), Menyah and Paudyal (2000) and Stoll (1989) relate the spread or the change in the spread to a vector of characteristics that are associated with the individual securities. These factors identified in prior spread models are the market value of the firm, the risk of the security (usually approximated by the standard deviation of returns), and trading volume.

The market value of the firm, is an important determinant of the spread since it reflects the depth of the demand for the stock. Traditionally high value firms enjoy deep markets for their stock. Their equity is traded frequently by a large number of agents, performance is closely monitored by analysts reducing the incidence of potential information asymmetry. These stocks are therefore highly liquid, as market makers need not expose their portfolios to the risk of adverse selection and unwanted inventory. Consequently, the equity of large firms is likely to enjoy lower spreads.

The influence of the risk of the security, proxied by the variance of returns, on the bid-ask spread is well documented by Roll (1984) and Karpoff (1986), who argue that as the risk of the stock is greater, market makers increase the spread because of two main reasons. First, if the stock bears a greater level of risk the market makers may find greater difficulty in trading the stock. Therefore in order to combat this greater cost of inventory, market makers increase the bid-ask spread. Second, the greater risk of the stock, may act as a signal to market makers that the number of informed traders increases, consequently leaving them at an informational disadvantage, resulting in the market makers increasing the bid-ask (Kim and Verrecchia (1994)).

Acker, Stalker and Tonks (2002) empirically examine the situation in which market makers are at an informational disadvantage with respect to informed traders around earnings announcements. The contribution of this paper is to extend Acker, Stalker and Tonks (2002) by examining the impact of market makers bid-ask spreads when they are faced with informational asymmetry with respect to informed traders throughout the year. This informational asymmetry is party captured by the volume of trading[1]. The theoretical motivation for an additional aspect is provided by Kim and Verrecchia who model market makers behavior surrounding an earnings announcement. Although the models reflect the setting specific of an earnings announcement, the underlying motivation applies to the situation faced by market makers at other times. Kim and Verrecchia show that the spread increases as market makers protect themselves from better-informed traders at earnings announcement dates. Specifically, they show that the spread is increasing in the diversity of opinion among investors. We use these insights of Kim and Verrecchia to augment the vector of characteristics in empirical models that empirically explain the spread by using the cross sectional variance of analysts' forecasts about a stock as a proxy for the diversity of opinion among investors.

The paper is organised as follows. In Section 2, we discuss in some detail the rationale for adding the variance of analysts' forecasts to the model of the spread. The data are discussed in Section 3. The adopted econometric methodology and the results are presented in Section 4. Finally section 5 contains our conclusions.

2. The impact of the variance of analysts' forecasts on the spread

A theoretical motivation for including the diversity of opinion in modelling the bid-ask spread is suggested by Kim and Verrecchia. Although the variance of returns captures the risk associated with holding the stock, it does not capture some of the information asymmetry between traders and market makers. Market participants differ in their ability to process information regarding the performance of the firm and consequently the market maker is unable to identify the type of agent that she is dealing with. She uses the total demand order to make inferences regarding the potential private information content residing in her total demand: Proposition 1 states:

> "The market is less liquid at the earnings announcement date than at nonearnings announcement dates. Moreover, market liquidity (the spread is lower) is increasing in the precision of public information, decreasing (the spread is higher) in the diversity of opinion among information processors and increasing in the number of non-discretionary liquidity traders. ….."
>
> (Kim and Verrecchia 1994, pp 53)

In an environment where the available information is noisy and there are benefits from further information processing, market makers know that they might be facing 'informed agents' that expect to realise profits from transacting with them[2]. The market maker cannot distinguish the type of trader she is dealing with, however she is aware of the process that determines the number of informed traders in the market. In a market where trading agents are facing fixed cost[3] C in order to process information over and above the noisy information in existence, the decision to undertake such expenditure will depend upon the marginal benefits of information processing.

The number of agents that become 'information processors' is the solution to the following equilibrium condition.

$$E(\Pi^x) - C = 0 \tag{1}$$

where $E(\Pi^x)$ denotes the expected profit from the acquired and processed information. Following the notation of Kim and Verrecchia, the number of agents (N) that decide to undertake expenditure C, is given as:

$$N = f(e, \theta, \rho, L, C) \tag{2}$$

where θ denotes the precision of all available information that is available to the public and $1-\rho$ $(0 < \rho < 1)$ represents the diversity of opinions among information processors. The numbers of uninformed liquidity traders is L who trade continuously and e is the variance of the forecast error contained in the processed signal.

Differentiation of (2) with respect to h and $1-\rho$ reveals that[4]

$$\frac{dN}{d\theta} < 0 \; \boldsymbol{and} \; \frac{dN}{d(1\text{-}\rho)} > 0 . \tag{3}$$

Thus the number of agents that are willing to undertake cost C in order to improve their forecast of the performance of the firm that emits a noisy signal Y is increasing with the imprecision of public information, therefore is decreasing as this information becomes less noisy and it is also increasing in the disagreement between the informed traders regarding the firm's outlook. Faced with an increasing variety of opinion expressed by analysts who follow a particular firm (and therefore are seen as informed traders), the market maker realises that the number of non-discretionary liquidity traders, whose information acquisition mimics her own, will decrease. She will be facing an increasing number of informed traders that have processed information and paid C in order to extract an excess return over the less informed agents.

In this situation in order to deter these traders from entering the market and trade in order to realise the small but significant information advantage, the market maker protects herself by reducing the liquidity of the stock. This is achieved by the increase of the bid-ask spread.

The above analysis means that when there is disagreement and by implication noisy information, then market makers are unlikely to have an information advantage over those traders who follow the stock closely. Therefore the market makers will increase the spread in order to protect themselves against the informed traders.

An important part of the research design is that we use the cross section variance of analysts forecasts as a proxy for the diversity of opinion amongst informed investors. The main motivation for using this proxy is the US study by Diether, Malloy and Scherbina (2002). For the period 1976-2000, they find that stocks for which there is a large variation in analysts' forecasts earn lower returns (than otherwise similar stocks). The explanation for this finding is that the variation reflects disagreement amongst analysts and that, as hypothesised by Miller (1977), prices will reflect the optimistic view whenever investors with the lowest valuations do not trade. More importantly, the finding is inconsistent with the hypothesis that dispersion amongst analysts' forecasts measures risk. The risk hypothesis predicts that high disagreement would be associated with higher returns. Prior research also supports the disagreement interpretation. Daley, Senkow and Vigeland (1988) find no association between the variance of analysts' forecasts and the ex post variance of returns during the announcement period. Gebhardt, Lee and Swaminathan (2001) include dispersion in analysts' forecasts as one of their proxies for risk to explain the implied cost of capital, but they find a negative relationship as in the Diether, Malloy and Scherbina (2002) study.

Based on the above discussion, the model to be estimated (and the expected signs) will be:

$$Spread_i = f(\underset{+}{VarF}, \underset{+}{Var\,\mathrm{Re}t}, \underset{-}{MrkVl}, \underset{-}{Vol}) \qquad (4)$$

where varF, the divergence of beliefs amongst analysts concerning the next earnings announcement, proxies for the likely exposure of market makers to the superior information of some traders; varRet, the ex post volatility of the stock over the forecast horizon, proxies for the expected volatility; MktVal is the firm's market value; and Vol is the trading volume.

3. The sample, data definitions and data collection

The companies chosen for the sample were those that had been in the FTSE Index over the entire duration of the estimation time period (1990-1999). This restriction makes available 26 companies and they are listed in the appendix.

The rationale for the restriction is based on the results of Beneish and Gardner (1995). They find that although trading volume does not increase when companies enter the Dow Jones Industrial Average Index, trading volume falls significantly and permanently when companies exit the index. Preliminary evidence (Gregoriou and Ioannidis, 2003) suggests that this finding translates to the FTSE 100 Index, which means that the coefficient on trading volume in our model is likely to change when companies re-enter the FTSE Index and therefore would bias our results. Although it would be possible to use companies for the first period during which they are included in the index, the number of observations would not be greatly enlarged.

The variance of analysts' forecasts, VarF.

The forecasts used are from the I/B/E/S Detail file, which gives information on company forecasts for the period 1990 and 1999 and forecasts for the sample companies are available for all the years. A total of 260 company-year observations were available at all the horizons investigated (h = 2, 4, 6, 8, 10 and 12 months before the year end). The variance of the forecasts for each company-year-horizon observation (VarF) is calculated from all the forecasts available during the month, the end of which is h months prior to the year end.

Calculation of the VarF variable on a monthly basis assumes that forecasts within each month are comparable. But the information set available to analysts will vary within each month. Therefore, since different analysts prepare their monthly forecasts at the different times of the month, this assumption of comparability is not strictly valid. However, the use of monthy data in is all that can be achieved. For example, Diether, Malloy and Scherbina (2002) use monthly stock returns to model the variation in analysts' forecasts.

The spread, S.

The bid-ask spread is calculated using the bid and the ask prices from Datastream. For all of the company-year-horizon combinations, the monthly bid and ask price was collected for the month, the end of which is h months prior to the year end.

Datastream uses end of month information to calculate a stock's spread for any date of the month. In contrast, analysts forecasts occur typically from the middle to the end of the month. Therefore, our estimate of the disagreement amongst analysts is not measured at the same point in time as the spread. We investigate this potential timing issue by obtaining daily bid-ask spreads and using them to calculate mid month spreads over the time period 1990-1999. The Spearman rank correlation between these mid month spreads and the end of the month spreads used in our analysis is 0.694. This result implies that the variation in the bid-ask spread throughout the month is relatively small.

Market value, MktVal.

The market value is calculated from Datastream. For all of the company-year-horizon combinations, the monthly market value was collected for the month, the end of which is h months prior to the year end.

Trading volume, Vol.

The trading volume data are calculated from Datastream. For all of the company-year-horizon combinations, the monthly trading volume was collected for the month, the end of which is h months prior to the year end. From 1997-1999 the market microstructure for trading FTSE100 stocks changed from a dealer system to an auction system. In the dealer market, the dealer is either the buyer or the seller in almost every trade. This procedure greatly overstates the actual number of trades between public investors. For example, consider the situation where Investor A sells 100 shares of stock to Dealer X and then later in the day Investor B purchases the same 100 shares from Dealer X. FTSE 100 reports trading volume of 200 shares for the stock, when only 100 shares actually changed hands between public investors. After 1997 the introduction of an auction trading system on the FTSE100 eliminated this problem because investors are the principals on both sides of a trade.

In order to provide comparable volume data, Datastream have adjusted the volume of trading prior to the structural break in order to be approximately consistent with the new dealer system after 1997. Consequently, our trading volume variable is not affected by this change in system.

A further issue in connection with the new dealer system is that it changed the bid-ask spread itself by making stocks more liquid. However, Ellul, Shin and Tonks (2002) and Cai, Hudson and Keasey (2004) show that most of this change in spread is accounted for by volume. Consequently, since our model includes volume as an explanatory variable, the new dealer system does not require any amendments to our model.

The variance of return, VarRet.

The variance of return is calculated from prices collected from Datastream. For all of the company-year-horizon combinations, the variance of return was estimated over the current month (the month for which all the other variables were collected) and the months from the horizon h to the year end.

The descriptive statistics for VarRet and VarF and the other regressors for the sample of 260 company year observations at each horizon are given in Table 1. One noticeable aspect of the table is the presence of skewness and kurtosis in both VarF and VarRet. Our approach to this is problem is to take natural logs of all the variables in the regressions to minimise the impact of these features.

A potential limitation of having a dataset, which requires a continuous membership of the FTSE100 index is that the dataset may be limited to stable firms since these firms have remained in the index over the entire duration of the sample period. However, this appears not to be the case with our sample. In the Atkins and Dyl (1997) study, the mean and standard deviation of the variance of return variable are 0.036 and 0.06 respectively for their NYSE sample and 0.10 and 0.35 respectively for their Nasdaq sample. In our Table 1, the mean and standard deviation of the variance of returns (VarRet) are 0.072 and 0.16 respectively[5]. That is, our sample has in fact more volatility than the Atkins and Dyl NYSE sample of over 11,000 observations. As expected, the volatility of returns in our sample is slightly smaller than the Atkins and Dyl Nasdaq sample. This suggests that our FTSE100 sample is not excessively stable relative to other FTSE100 companies which are not included in our sample. The comparison of our sample with the NYSE sample of Atkins and Dyl also indicates that our sample is representative not only of those omitted from the FTSE100, but also of those outside of it.

[INSERT TABLE 1 HERE]

4. Econometric methods and results

Our adopted linear specification is of the form:

$$Spread_{iht} = \beta_1 + \beta_2 VarF_{iht} + \beta_3 Var\,\mathrm{Re}\,t_{iht} + \beta_4 MktVal_{ih} + \beta_5 Vol_{iht} + \varepsilon_{it} \tag{5}$$

where: $Spread_{ih}$ is the bid-ask spread for stock i at horizon h before the end of year t; $VarF_{ih}$ is the variance of analysts forecasts for stock i at horizon h before the end of year t; $VarRet_{ih}$ is the expost variance of monthly returns for stock i, at horizon h before the end of year t; $MktVal_{ih}$ is the market value of firm i at horizon h before the end of year t; and Vol_{ih} is the trading volume of stock i at horizon h before the end of year t. Given the previous analysis we expect that $\beta_4, \beta_5 < 0$ and $\beta_2, \beta_3 > 0$. The possible endogeneity[6] of Vol_{ih} requires the Hausman (1978) test statistic to establish the choice of a consistent estimator. The inappropriate use of Instrumental Variables (IV) will result in severe loss of efficiency compared to the least squares estimator. The test statistic is based on the difference between the two estimators that are consistent under the null hypothesis but only one of them, the IV estimator is consistent under the alternative. The test statistic is given by:

$$H = \left(b_{IV} - b_{LS}\right)' \left\{\left(\hat{X}'\hat{X}\right)^{-1} - \left(X'X\right)^{-1}\right\}^{-1} \left(b_{IV} - b_{LS}\right) / s^2 \tag{6}$$

where $\hat{X}$ denotes the matrix of regressors where the 'endogenous' variables have been instrumented, X the original matrix of regressors and s^2 the variance estimate. This Wald statistic follows the chi-square distribution with K, the number of instrumented variables, degrees of freedom. Using as additional instruments current and lagged returns and lagged spread, following the methodology of Atkins and Dyl (1997), the resulting value of the statistics was 2.34. We were therefore unable to reject the null hypothesis that both estimators were consistent, and given that the Least Squares Estimator (LS) is efficient we proceed to estimate the model by LS.

The results of our model for horizons 2, 4, 6, 8, 10, and 12 are given in Table 2. For all horizons, all the variables are significant except for *VarF* at horizons longer than 6 months.

[INSERT TABLE 2 HERE]

Consistent with Atkins and Dyl (1997), the coefficient on market value, *MktVal,* is negative, indicating that larger companies have a smaller spread. The coefficient on ex post volatility, *VarRet,* is positive, indicating that market makers anticipate the relative volatility's of stocks and use this information in setting their spreads. It is also of interest that the elasticity with respect to MktVal is large, indicating that size variations are important even within the FTSE100.

In addition to the market value, the trading volume, *Vol,* is significant and negative indicating that a larger volume of trade is associated with a smaller spread. This finding is consistent with Glosten and Harris (1988) who argue that the spread reacts to volume as market makers attempt to maintain their inventory targets.

An important result is that the variance of analysts' forecast *VarF* which is intended to capture the disagreement amongst traders about the future of the stock, is also significant and positive. This suggests that as disagreement rises, market makers increase the spread to protect themselves against any temporary information advantage which investors may have. This provides strong support for the hypothesis of the Kim and Verrecchia model of how market makers respond to disagreement.

However, *VarF* is significant only for horizons up to 6 months; for 8, 10 and 12 month horizons *VarF* does not help to explain spread. The reason for this finding relates to a well known characteristic of analysts' forecasts initially identified by Brown and Rozeff (1978) and then subsequently by Dimson and Marsh (1984) and Stickel (1989). The studies find that the superior information held by analysts relates to the short term. Even when analysts forecast for 12 months ahead, their information advantage relates to the earlier part of the horizon. Therefore, it is not surprising that for long horizons the market maker does not infer information from the disagreement amongst analysts.

Table 2 also reports diagnostic statistics. There are no signs of heteroscedasticity or non linearity, but there is evidence of non normality in the residuals (for horizons 2, 4, 6 & 10). Non normality in the residuals may mean that the distribution is "fat-tailed" or contains outliers.

In the general linear model

$$y_i = X_i\beta + u_i \tag{7}$$

when the errors are not normally distributed the least squares estimator b is no longer efficient of asymptotically efficient although it is still consistent. As the respective distribution of b and $(T-K)\left(\frac{\hat{\sigma}^2}{\hat{\sigma}}\right)$ are no longer normal and chi-square respectively, the usual F and t-tests on β are not necessarily valid in small samples, as they may suffer loss of power due to severe deviation from normality. This has led to the adoption of a class of estimators that are more robust than least squares in the sense that maintain their efficiency irrespectively of the underlying error distribution (Judge, Griffiths, Hill, Lutkepohl and Lee 1988 p836). In general these estimators obtain an estimate of β by solving the asymmetric least absolute deviations

$$\min\ T^{-1}\sum_{i=1}^{T} l_p\left|y_i - \beta' X_i\right| \tag{8}$$

where p denotes the pth conditional quantile of y_i given $X_i = x$ and

$l_p(u) = \left[p - 1\{u \prec 0\}\right]|u|$, for $p = 0.5$ we obtain the function shown in equation (8).

A solution to the above is called the Least Absolute Deviations (LAD) or median regression estimate. It can be shown that

$$\sqrt{T\left[b(.5) - \beta\right]} \rightarrow N\left(0, \{2f(0)\}^{-2} Q^{-1}\right) \tag{9}$$

where $Q = T^{-1}(X'X)$ and $\{2f(0)\}^{-2}$ denotes the asymptotic variance of the sample median, this class of estimator will be more efficient that the least squares estimators in distributions where 'outliers' are prevalent.

Given that the exact form is unknown we use the LAD regression to obtain robust results for horizons 2, 4, 6 and 10. These results are given in Table 3 and support the conclusions of Table 2.

[INSERT TABLE 3 HERE]

As expected, there is a modest increase in the equations' explanatory power. More importantly, the size and standard errors of the estimated coefficients remain unaltered; in particular, *VarF* is significant but only for horizons up to 6 months, as in

Table 2. One noticeable difference is that the coefficients on *MktVal* are reduced, although they are still considerably larger than those on the other variables.

4.1 Robustness Checks

To ascertain the validity of the results documented thus far we employ additional regression tests to demonstrate robustness.

A. Mis-measurement of analyst disagreement, VarF.

From the appendix, we can see that 7 companies have fewer than 10 analysts following the stock for some months during the sample period. For these companies, the small number of observations may result in large jumps in analyst disagreement variable (VarF). In order to assess the impact of this potential problem we re-estimate equation 5 excluding these 7 companies. The results can be seen in Table 4. The results are very similar to those of Table 2 and suggest that the results are robust to this potential problem[7].

[INSERT TABLE 4 HERE]

Another way of dealing with the potential measurement problems in the estimation of analyst disagreement is to remove the outlier observations on the explanatory variable, *VarF*. This was accomplished by removing observations in both the 5% tails of the distribution of *VarF*. Table 5 gives the results after excluding these observations. We can see that the results are practically identical to those of Table 2. This is not surprising since the removed observations account for only 8 observations and suggests that the data do not suffer from problems of extreme values.

[INSERT TABLE 5 HERE]

B. The Lag in the Variance of Analysts' Forecasts

One assumption made in our model, equation 5, is that the spread is contemporaneously related to the diasgreement amongst analysts (VarF). Diether, Malloy and Scherbina (2002) suggest that market makers may take some time to adjust to the analysts' disagreement and therefore it may be appropriate to use lagged VarF as the measure of disagreement. We re-estimate equation 5 using the previous month's measure of disagreement as an explanatory variable. The results can be seen in Table 6. We can see from Table 6 that the results of Table 2 remain intact[8] suggesting that analysts' disagreement is relatively stable from one month to the next.

[INSERT TABLE 6 HERE]

5. Conclusions and further work

In this study we have estimated a linear equation that explains the bid-ask spread in the UK equity market for the permanent members of FTSE100 companies over the period 1990-1999. The contribution of equation lies in the establishment of the statistical significance of the variance of the analysts' forecasts in the presence of other exogenous variables that are regularly included in the modelling of the spread. We find that published disagreement amongst analysts affects the behaviour of market makers and they act to prevent trade from informed traders by increasing the spread. The motivation for including the variance of the analysts' forecasts is provided by Kim and Verrecchia (1994) who show that market makers will widen the spread to protect themselves from informed investors, and by Diether, Malloy and Scherbina (2002) who find that the dispersion of analysts' forecasts proxy for their differences of opinion about a stock.

In our estimated model we have extended the model of Atkins and Dyl (1997) where they find that both the volatility of returns variable reflects the risk to which the market maker is exposed and market size are important by adding trading volume and the disagreement among analysts regarding earnings. The role of volatility in explaining the spread is a dual one: first, disagreement leaves market makers at a disadvantage with respect to informed traders (Kim and Verrecchia, 1994) and secondly, high dispersion stocks earn lower returns whilst the uncertainty is being resolved (Diether, Malloy and Scherbina, 2002) this is because these stocks have to be held for longer time periods thus reducing their liquidity.

We find that both volatility of returns and disagreement amongst analysts are significant (with the hypothesised signs) in explaining FTSE 100 company spreads. The volatility captures information uncertainty concerning the current period to the year end. Since company returns are affected by the market in general, it is also likely that volatility reflects economy wide aspects of uncertainty. However, our results show that the disagreement amongst analysts is also significant. What interpretation should be placed on this? First, it is worth noting that disagreement is more likely to be related to firm specific issues in contrast to the volatility measure which is likely to be driven by market wide factors. As a consequence, we suggest that disagreement by investors is potentially related to the probability of poor results beyond the information contained in the volatility of returns. Such performance is well known to cause delays in reporting the year end results and causes additional information asymmetry between market makers and investors. The market makers in turn increase their spread in order to protect themselves as modelled in Kim and Verrecchia (2001).

Extensions of the work along similar lines is to incorporate an event study looking at the effect of revisions in analyst forecasts on spreads. Krinsky and Lee (1996) find that the asymmetric component of the bid-ask spread increases around an earnings announcement, where the information asymmetry is captured by the volatility of the market. As a direct consequence of the empirical evidence in this paper, we would expect the bid-ask spread to increase further around an earnings announcement due to the increase in the disagreement of analysts' forecasts for short horizons.

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TABLE 1: Descriptive statistics for the variance of analysts' forecasts (VarF), the variance of returns (VarRet), the market value of firms (MktVal) and trading volume (Vol) for horizons of 2, 4, 6, 8, 10, and 12 months.

	Horizon	*2 months*	*4 months*	*6 months*	*8 months*	*10 months*	*12 months*
VarF							
Mean		2.51	5.83	3.71	3.54	3.21	3.13
Standard Deviation		8.51	13.20	11.87	11.62	11.51	11.46
Minimum		0.00	0.00	0.00	0.00	0.00	0.00
Maximum		67.72	108.82	81.10	64.24	65.67	66.78
Skewness		5.42*	4.30*	4.42*	4.75*	4.23*	4.64*
Kurtosis		31.60*	23.19*	22.42*	23.76*	21.12*	19.82*
No of observations		260	260	260	260	260	260
	Horizon	*2 months*	*4 months*	*6 months*	*8 months*	*10 months*	*12 months*
VarRet							
Mean		5.64	6.78	6.26	7.67	7.51	7.62
Standard Deviation		12.76	14.53	13.80	16.39	14.67	16.04
Minimum		0.00	0.00	0.00	0.00	0.01	0.00
Maximum		99.21	83.87	95.29	99.44	119.08	95.68
Skewness		4.73*	4.63*	4.43*	4.82*	4.65*	4.68*
Kurtosis		23.23*	22.76*	21.54*	22.20*	24.78*	19.32*
No of observations		260	260	260	260	260	260

	Horizon	*2 months*	*4 months*	*6 months*	*8 months*	*10 months*	*12 months*
MtkVal							
Mean		8048.293	8069.331	8800.68	8900.16	8960.76	9901.21
Standard Deviation		754.45	799.69	811.01	832.46	843.23	873.43
Minimum		2371.1	2381.39	2400.12	2432.89	2554.32	2764.76
Maximum		97644.13	93354.18	95544.12	99233.65	120032.21	131032.21
Skewness		0.83	-0.60	0.72	0.65	-0.54	0.82
Kurtosis		-0.68	-0.044	0.58	0.28	-0.067	0.70
No of observations		260	260	260	260	260	260
	Horizon	*2 months*	*4 months*	*6 months*	*8 months*	*10 months*	*12 months*
Vol							
Mean		622572	732570	742679	753565	777433	876231
Standard Deviation		215480	226440	237480	246540	278340	288231
Minimum		446920	446920	446920	446920	446920	446920
Maximum		899630	999630	999687	1096300	1145300	1165542
Skewness		0.45	0.55	0.65	0.65	0.76	0.82
Kurtosis		-0.79	-0.69	-0.65	-0.86	-0.45	-0.99
No of observations		260	260	260	260	260	260

Notes:

* Indicates that the test of the null hypothesis of no skewness and no kurtosis is rejected at the 5% level of significance. The tests used for skewness and kurtosis are those proposed by Jacque and Bera (1980) .

TABLE 2: OLS estimates of the exposure model of bid-ask spread.

$$Spread_{ih} = \beta_1 + \beta_2 VarF_{ih} + \beta_3 Var\,\mathrm{Re}\,t_{ih} + \beta_4 MktVal_{ih} + \beta_5 Vol_{ih} + \varepsilon_{ih}$$

Horizon	β_1	β_2	β_3	β_4	β_5	$\bar{R}^2$	N
2	0.52(0.08) **6.5***	0.14(0.03) **4.67***	0.18(0.07) **2.57***	-5.24(2.31) **-2.27***	-0.62(0.23) **-2.70***	0.153	260
4	0.51(0.08) **6.34***	0.15(0.06) **2.50***	0.17(0.03) **5.85***	-3.97(1.91) **-2.08***	-0.51(0.23) **-2.22***	0.185	260
6	0.53(0.08) **6.63***	0.15(0.06) **2.50***	0.19(0.03) **6.33***	-3.58(1.71) **-2.09***	-0.57(0.24) **-2.38***	0.190	260
8	0.46(0.08) **5.75***	0.06(0.05) **1.20**	0.17(0.07) **2.43***	-4.47(2.14) **-2.09***	-0.71(0.34) **-2.09***	0.149	260
10	1.89(0.37) **5.11***	0.24(0.17) **1.41**	0.39(0.08) **4.78***	-3.79(1.72) **-2.20***	-0.77(0.31) **-2.48***	0.147	260
12	0.53(0.08) **6.63***	0.05(0.03) **1.50**	0.16(0.07) **2.29***	-3.78(1.85) **-2.04***	-0.76(0.34) **-2.24***	0.10	260

The standard errors are shown in brackets.

The t statistics are shown in bold and * indicates significance at the 5% level.
All the variables in the above equation are expressed as natural logarithms.

Diagnostic results

Horizon	Heteroscedasticity Test	Normality Test	Functional Form Test
2	1.02	33.43*	0.71
4	1.02	54.91*	1.27
6	0.67	141.40*	1.28
8	1.20	5.24	0.60
10	1.72	15.81*	0.65
12	1.38	3.38	0.15

Notes:

All the diagnostic statistics that are reported are based on the F statistic.
The heteroscedasticity test is based on a regression of squared residuals on squared fitted values. The test we use is the test proposed by White (1980).

The normality test is based on a test of skewness and kurtosis of the residuals. The test we use is the one proposed by Jacque and Bera (1987). * indicates the rejection of the null hypothesis of normally distributed residuals at the 5% level of significance.

The functional form test, is a test to see whether the model is linear or not. The test used is Ramsey's 1969 reset test, which uses the square of the fitted values.

TABLE 3: Robust (least absolute deviation) estimation of the exposure model of bid-ask spread.

$$Spread_{ih} = \beta_1 + \beta_2 VarF_{ih} + \beta_3 Var\,\mathrm{Re}t_{ih} + \beta_4 MktVal_{ih} + \beta_5 Vol_{ih} + \varepsilon_{ih}$$

Horizon	β_1	β_2	β_3	β_4	β_5	$\overline{R}^2$	N
2	0.37(0.06) **6.17***	0.14(0.02) **7.00***	0.28(0.05) **5.6***	-1.41(0.68) **-2.27***	-0.35(0.13) **-2.69***	0.183	260
4	0.47(0.06) **7.83***	0.16(0.02) **2.50***	0.26(0.05) **5.20***	-2.29(0.91) **-2.52***	-0.65(0.23) **-2.83***	0.195	260
6	0.45(0.06) **7.50***	0.16(0.02) **8.00***	0.25(0.05) **5.00***	-2.60(0.94) **-2.77***	-0.67(0.24) **-2.79***	0.206	260
10	1.29(0.27) **4.81***	0.62(0.75) **0.83**	0.20(0.08) **2.50***	-2.07(0.72) **-2.88***	-0.69(0.28) **-2.46***	0.150	260

Notes:

The standard errors are shown in brackets.

The t statistics are shown in bold and * indicates significance at the 5% level.
All the variables in the above equation are expressed as natural logarithms.

TABLE 4: OLS estimates of the exposure model of bid-ask spread excluding companies with less than 10 analysts following the stock.

$$Spread_{ih} = \beta_1 + \beta_2 VarF_{ih} + \beta_3 Var\,\mathrm{Re}\,t_{ih} + \beta_4 MktVal_{ih} + \beta_5 Vol_{ih} + \varepsilon_{ih}$$

Horizon	β_1	β_2	β_3	β_4	β_5	$\overline{R}^2$	N
2	0.59(0.08) **7.38***	0.21(0.05) **4.2***	0.26(0.07) **3.71***	-5.29(2.31) **-2.29***	-0.61(0.24) **-2.54***	0.174	190
4	0.56(0.07) **8.00***	0.28(0.04) **7.00***	0.29(0.07) **4.14***	-3.87(1.90) **-2.04***	-0.57(0.21) **-2.71***	0.193	190
6	0.53(0.07) **7.57***	0.29(0.05) **5.8***	0.22(0.05) **4.4***	-3.51(1.70) **-2.06***	-0.54(0.26) **-2.08***	0.212	190
8	0.50(0.08) **6.25***	0.17(0.12) **1.42**	0.19(0.09) **2.11***	-4.42(2.11) **-2.09***	-0.69(0.35) **-1.97***	0.164	190
10	0.57(0.07) **8.14***	0.18(0.11) **1.64**	0.32(0.09) **3.56***	-3.71(1.73) **-2.14***	-0.78(0.31) **-2.52***	0.159	190
12	0.56(0.09) **6.22***	0.12(0.11) **1.09**	0.22(0.09) **2.44***	-3.74(1.85) **-2.02***	-0.75(0.34) **-2.21***	0.17	190

The standard errors are shown in brackets.

The t statistics are shown in bold and * indicates significance at the 5% level.
All the variables in the above equation are expressed as natural logarithms.

TABLE 5: OLS estimates of the exposure model of bid-ask spread excluding observations in both the 5% tails of the distribution of $VarF$.

$$Spread_{ih} = \beta_1 + \beta_2 VarF_{ih} + \beta_3 Var\,\mathrm{Re}\,t_{ih} + \beta_4 MktVal_{ih} + \beta_5 Vol_{ih} + \varepsilon_{ih}$$

Horizon	β_1	β_2	β_3	β_4	β_5	$\overline{R}^2$	N
2	0.52(0.08) **6.5***	0.14(0.03) **4.67***	0.18(0.07) **2.57***	-5.24(2.31) **-2.27***	-0.62(0.23) **-2.70***	0.152	252
4	0.51(0.08) **6.34***	0.15(0.06) **2.50***	0.17(0.03) **5.85***	-3.97(1.91) **-2.08***	-0.51(0.23) **-2.22***	0.186	252
6	0.53(0.08) **6.63***	0.15(0.06) **2.50***	0.19(0.03) **6.33***	-3.58(1.71) **-2.09***	-0.57(0.24) **-2.38***	0.191	252
8	0.46(0.08) **5.75***	0.06(0.05) **1.20**	0.17(0.07) **2.43***	-4.47(2.14) **-2.09***	-0.71(0.34) **-2.09***	0.149	252
10	1.89(0.37) **5.11***	0.24(0.17) **1.41**	0.39(0.08) **4.78***	-3.79(1.72) **-2.20***	-0.77(0.31) **-2.48***	0.148	252
12	0.53(0.08) **6.63***	0.05(0.03) **1.50**	0.16(0.07) **2.29***	-3.78(1.85) **-2.04***	-0.76(0.34) **-2.24***	0.11	252

The standard errors are shown in brackets.

The t statistics are shown in bold and * indicates significance at the 5% level.

All the variables in the above equation are expressed as natural logarithms.

TABLE 6: OLS estimates of the exposure model of bid-ask spread using lagged analysts forecasts.

$$Spread_{iht} = \beta_1 + \beta_2 VarF_{iht-1} + \beta_3 Var\,\mathrm{Re}\,t_{iht} + \beta_4 MktVal_{ih} + \beta_5 Vol_{iht} + \varepsilon_{iht}$$

Horizon	β_1	β_2	β_3	β_4	β_5	$\overline{R}^2$	N
2	0.55(0.09) **6.11***	0.09(0.04) **2.25***	0.21(0.08) **2.63***	-5.27(2.33) **-2.26***	-0.64(0.25) **-2.56***	0.149	259
4	0.53(0.08) **6.63***	0.08(0.04) **2.00***	0.19(0.07) **2.71***	-3.94(1.92) **-2.05***	-0.53(0.22) **-2.41***	0.181	259
6	0.51(0.07) **7.29***	0.09(0.04) **2.25***	0.18(0.05) **3.6***	-3.54(1.70) **-2.08***	-0.56(0.25) **-2.24***	0.189	259
8	0.48(0.09) **5.33***	0.07(0.06) **1.17**	0.18(0.08) **2.25***	-4.49(2.15) **-2.09***	-0.72(0.35) **-2.06***	0.146	259
10	1.92(0.38) **5.05***	0.27(0.19) **1.42**	0.37(0.09) **4.11***	-3.75(1.73) **-2.17***	-0.75(0.32) **-2.34***	0.142	259
12	0.55(0.09) **6.11***	0.06(0.04) **1.50**	0.18(0.08) **2.25***	-3.76(1.86) **-2.02***	-0.78(0.35) **-2.23***	0.08	259

The standard errors are shown in brackets.

The t statistics are shown in bold and * indicates significance at the 5% level.

All the variables in the above equation are expressed as natural logarithms.

Appendix

The 26 companies used in our dataset with the corresponding mean number of analysts that follow each company are the following:

Company Name	Mean number of Analysts	Minimum number of Analysts	Maximum number of Analysts
ABBEY NATIONAL	28.8	3.87	54.32
ALLIED DOMECQ	29.8	20.56	37.98
PRUDENTIAL	30	15.91	42.71
SCHRODERS	29.3	11.93	40.73
ARM HOLDINGS	28.4	20.43	49.01
POWERGEN	28.6	3.58	58.91
BAA	28.8	13.04	46.88
SAFEWAY (UK)	31	7.33	48.35
BOOTS	32.5	9.6	43.23
BP	32	13.49	40.64
BRITISH AIRWAYS	32.3	16.14	43.05
TESCO	31.9	11.42	42.08
BRITISH TELECOM	30.07	16.89	35.44
CAPITA GROUP	33	19.04	38.91
SAINSBURY (J)	29.8	17.24	42.04
CENTRICA	27.1	15.56	45.61
COMPASS GROUP	27.8	12.5	44.23
DAILY MAIL 'A'	32.5	4.35	52.04
HSBC HOLDINGS	31.4	3.81	46.20
DIXONS GP.	30.1	14.17	41.72
ELECTROCOMP.	29.7	16.13	38.79
EMI GROUP	36.6	14.19	44.93
VODAFONE GROUP	32.4	16.3	40.95
SAGE GROUP	30	16.01	47.32
HANSON	29.6	7.81	53.97
GRANADA	34.2	15.77	43.84

Notes:

The mean number of analysts are computed as the mean number of analysts that follow each company over all the horizons.

NOTES

[1] Note that the influence of the disagreement of analysts forecasts is not entirely captured by changes in trading volume because trading volume will not necessarily increase when the number of informed traders increases. Trading volume will only increase if uniformed traders have access to the information of informed traders and consequently replicate their trades.

[2] In Kim and Verrecchia (1994) the noise occurs due to the impact of the earnings announcement. In our study the noisy periods which occur throughout the year are defined as a continuous variable which is captured by the degree of analysts' disagreement.

[3] The nature of the cost is such that independently of the possible variance reduction of the noisy public signal the agent will pay C.

[4] The exact solution to the problem is given as: $0 = N\theta(N+1+\{2+(N-1)\rho\}e\theta^2) - \frac{L(1+e\theta)}{C^2}$.

[5] For comparability with Atkins and Dyl we use our 12 month horizon descriptive statistics.

[6] Both the bid-ask spread and trading volume are measures of liquidity. This implies that they may be simultaneously determined resulting in the endogeneity of trading volume (Heaton and Lucas (1996) and Vayanos (1998)).

[7] We would like to thank an anonymous referee for suggesting this point.

[8] Tables 4, 5 and 6 report the OLS results of the robustness check. The Least Absolute Deviation results are very similar to the OLS results, but are not reported here but are available upon request.