Trading Activity and Stock Price Volatility:
Evidence from the London Stock Exchange

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Abstract

Analysis of FTSE 100 stock transactions data reported by the London Stock Exchange shows that trade frequency and average trade size impact price volatility for small trades (i.e. trades of one NMS or less). For large trades, only trade frequency affects price volatility. In further splitting small trades by relative size, trade frequency and average trade size are found to affect price volatility only for trades close to stocks' maximum guaranteed quoted depth. This evidence is consistent with microstructure models of dealer inventory adjustment and strategic behavior by informed traders, where dealers and uninformed traders face adverse selection costs.

1. Introduction

Jones, Kaul, and Lipson (1994) (JKL) reports a startling result concerning stock price volatility. After decomposing trading volume into two components, they find that the number of trades (trade frequency) is much more important than trade size in affecting stock price volatility. Their evidence is based on an examination of a large sample of Nasdaq stocks using daily data over the 1986-1991 period, and aggregated into equity capitalization quintiles. This evidence appears to run counter to the dominant market microstructure theories of stock price determination, which emphasize the role of trade size as a means of detecting likely informed trading and adverse selection. We assess the generality of the JKL conclusions by studying this relation in another major competing dealer market, the London Stock Exchange (LSE). We then relate our findings to investors' strategic trading behavior and to the structural design of the LSE.

The LSE is an attractive dealer market to study since it exhibits decidedly different characteristics from the Nasdaq market. The LSE differs in terms of market participants, trade reporting requirements, internal exchange rules and stock market regulation. In particular, unlike the Nasdaq, trading activity on the LSE is concentrated in the hands of a small number of dominant dealers and institutional traders.

To examine the question of how trading activity impacts price volatility, we analyze daytime and hourly price changes and trading activity for the larger stocks in the London market. Our daytime results are consistent with the JKL results for Nasdaq stocks. JKL show that their results are highly robust to a variety of alternative specifications. Our approach is to use the JKL specification and examine whether the LSE yields similar evidence. In addition, we investigate whether the dominant influence of trade frequency on stock price volatility is due to the trading activity patterns of investors seeking to exploit the guaranteed quoted depth in the market. These investors could be trading strategically or simply seeking liquidity. Examples are dealers making smaller trades in the inter-dealer market to offset the impact of recent large block trades and investors trading large blocks, who breakup their trades to gain greater liquidity.

We also explore two extensions of the basic JKL experiment. First, we consider whether time aggregation of individual trades into daily sums and averages strongly smoothes the underlying variability of the trade size variable, thereby lowering its information content and significance. To see this, suppose that only one large trade occurs in the day, along with many small liquidity or noise trades. The impact of the one large trade on average trade size would be inversely related to the frequency of trades during the day. Thus, aggregating transactions over time can dilute the explanatory power of the trade size variable. At the other end of the spectrum, when a trade by trade analysis is conducted, only the trade size variable can explain the time series pattern in stock price volatility, since the number of trades is almost always one. Given these concerns, we also examine hourly data to increase the potential explanatory power of the average trade size variable.[1]

Second, we consider the fundamental question of whether trades of all sizes have the same effect on price volatility. If information traders break up large trades to gain better price execution, then any remaining large trades are likely to be liquidity driven, with little impact on price volatility. Barclay and Warner (1993) present evidence consistent with information traders intentionally breaking up large orders, thus making large trades less frequent and medium size trades more informative.[2] This is referred to as the stealth trading hypothesis. Further attenuation of the empirical relation between trade size and price volatility can result from an infrequency of large trades relative to small trades, potential front running prior to the completion of large trades, reporting of some contemporaneous small trades as a single large trade and delayed reporting of large trades. Therefore, in analyzing the trading activity-price volatility relation, we also investigate the empirical relevance of trade size categories and of trade reporting rules.

In previewing our results, we document daytime evidence similar to that reported by JKL. Specifically, stock price volatility is positively correlated with either the number of trades or average trade size. When we jointly examine the partial correlations of these two variables with stock price volatility, we find that only the number of trades is statistically significant on a consistent basis. Unlike JKL, we also find that the strength of the relation between price volatility and trading activity is much weaker in the London market, which may reflect the larger size and institutional nature of most trading activity taking place in this venue.

We explore the sensitivity of the results to hourly aggregation and to trade size categories. Specifically, we separate trading activity variables into trades that are above the maximum guaranteed depth of current quotes from trades at or below that depth to assess whether differences occur in the price volatility-trading activity relation across

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[1]Combining overnight and daytime volatility into daily volatility may also weaken the explanatory power of the daytime trading activity variables. For example JKL regress daily volatility on daytime trading activity variables.

[2]They present evidence based on NYSE stock price data, which is consistent with this perspective.

trades of varying sizes. We further decompose small trades into those much smaller than the maximum guaranteed depth and trades near this depth, but not exceeding it. The resulting evidence shows that trades at the maximum guaranteed depth are most influential. Our results are consistent with Barclay and Warner's conclusions that these trades represent a disproportionate amount of informed trading. These results are found to be insensitive to alternative trade size measures. They are also robust to grouping stocks into different equity capitalization and trading volume categories.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature and evidence. The market setting, the data set, and its key statistical properties are described in Section 3. In section 4, we explain our methodological approach. Section 5 presents our empirical evidence on the relation between stock price volatility and the number of trades and average trade size for several alternative measures of price volatility, number of trades and trade size. In Section 6, we test whether the price volatility–trading activity relation found in Section 5 is consistent with the stealth trading hypothesis. Section 7 summarizes our findings and draws conclusions.

2. Literature Review

A review of market microstructure theory shows that trade size is linked to information arrival and price volatility. Glosten and Milgrom (1985) develop a sequential trading model with informed and uninformed investors and find that market makers and uninformed investors experience adverse selection when trading with informed investors. By assumption, each investor is allowed to transact one unit of stock per unit of time, so price changes are completely independent of trade size. Easley and O'Hara (1987) extend this model to allow traders to transact at varying trade sizes and by introducing uncertainty in the information arrival process of the informed trader. When investors act competitively, Easley and O'Hara find that larger sized trades tend to be executed by better informed investors, so that larger trades exhibit a greater adverse selection effect. Thus, there is a positive relation between trade size and price volatility.

In critically evaluating the Easley and O'Hara model, theorists have observed that traders are not allowed to act strategically, which could result in large blocks being broken up into a number of smaller trades. If informed investors are allowed to strategically breakup orders as in Kyle (1985), Amati and Pffleiderer (1988), Foster and Vishwanathan (1990) and Back (1992), then the effect of trade size on price volatility is attenuated and its impact may be shifted to the number of trades. Supporting this view, Barclay and Warner (1993) report empirical evidence from the NYSE consistent with informed investors breaking up large trades so as to better hide their information motivated trading activity. Their evidence is based on how influential trades of various sizes are on price changes. This evidence suggests the need to investigate whether price volatility reacts differently to trades depending on their size category.

Empirical evidence of a positive relation between share volume and stock price volatility is documented by a number of researchers using a variety of methods. Karpoff (1987) surveys the early evidence, which is based on monthly, weekly and some daily stock return studies. More recent support for this relation is found in Jain and Joh (1988), Schwert (1989), Gallant, Rossi, and Tauchen (1992, 1993), Lang, Litzenberger, and Madrigal (1992), Lamoureux and Lastrapes (1994), Foster and Viswanathan (1995), and

Andersen (1996). It should be noted that nearly all of the more recent evidence is based on daily stock returns in the U.S.

JKL analyze stock price volatility on Nasdaq market and find that trade size appears to have an immaterial effect, once the number of trades is taken into account. This conclusion appears to be at variance with the prior empirical evidence. Karpoff (1987) reviews the earlier literature (prior to JKL) and reports that stock price volatility is positively related to trading volume. However, these earlier studies typically do not consider competing measures of trading activity, nor do they examine the number of trades as a measure of trading activity. Surprisingly, the JKL study has not elicited much subsequent analysis to assess the robustness of its evidence or the generality of its conclusions. This study directly addresses these important questions and concludes that market structure and stealth trading are likely explanations for JKL's findings, at least as they pertain to the LSE.

While the JKL findings are important enough to warrant serious examination, their conclusions have also reinforced a tendency by many researchers to use share turnover or the number of trades as a sufficient statistic for trading activity or market liquidity. In many earlier empirical studies of market microstructure and price volatility, researchers have relied on single measures of trading activity. For example, Lakonishok and Lev (1987) used turnover as their sole measure of liquidity in examining the effects of stock splits. In more recent work, Hu (1997) studies the cross sectional relation between stock returns and turnover on the Tokyo Stock Exchange. He finds a negative relation between returns and turnover and argues that turnover is a useful measure of liquidity.[3] Before the profession presumes that the number of trades is a sufficient statistic for trading volume or market liquidity, some additional rigorous empirical verification is needed. Thus, it is important to carefully assess whether it is indeed the case that the number of trades is an appropriate proxy for these other economic variables. This study speaks to this question by examining whether the number of trades is a sufficient statistic for trading activity as it impacts stock price volatility.

3. Institutional Background and Data Description

We analyze the stocks comprising the dominant market index on the LSE, the Financial Times Stock Exchange (FTSE-100) index in 1995, before the 1997 adoption of the Stock Exchange Trading System.[4] This index is composed of the 100 largest domestic stocks based on equity capitalization, which in recent years has represented about 70% of the total equity capitalization of all U.K. stocks. We analyze both daytime and hourly data. These data are obtained from monthly CD ROM files produced by the LSE, which we combine into an annual file and then extensively check for data errors.[5]

Similar to the Nasdaq market in structure, the LSE has a competing dealer market structure, lacks an integrated limit order book and has no separate upstairs market for

[3]Also, see the recent articles by Lo and Wang (2000), Datar, Naik, and Radcliffe (1998), Cleassens, Dasgupta, and Glen (1998).

[4]We select all stocks in the FTSE-100 index as of the start of our observation period, i.e. January 2, 1995. Due to several mergers of these stocks, we lose two stocks in November and December.

[5]See Board and Sutcliffe (1995) and Reiss and Werner (1996) for a more extensive discussion of the file structures and peculiarities of the LSE transaction files.

large block trades.[6] Unlike the Nasdaq, the LSE is basically an institutional club with five big market makers and five big institutions. The LSE is officially open from 8:30 a.m. until 4:30 p.m. London (BST) time.[7] When the stock exchange is officially open, firm quotes on all stocks in the FTSE-100 are available for transactions of 5,000 to 100,000 shares or more. Under LSE rules, all dealers making a market in tier 1 stocks (which includes all the FTSE 100 stocks) must make their bid and ask quotes good for the stock's typical trade size, called its *normal market size* (NMS). This minimum quote size varies across stocks, reflecting each stock's normal market depth. As a practical matter, one can approximate a stock's NMS by the mode of the depth from all quotes in the stock for the prior *month*.[8]

The LSE database includes all stock transactions by customers and dealers, which we aggregate to obtain hourly and daily numbers of trades, their pound values, and the number of shares involved.[9] Trading activity figures include both customer trades and inter-dealer trades. The LSE transactions database also distinguishes between buy and sell orders. To avoid double counting the buy and sell sides of each trade, we only use buy orders to measure trading activity variables. Our data covers the 242 trading days in

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[6]See Schwartz (1991), Huang and Stoll (1991) and Masulis and Ng (1995) for further description of the trading structure and procedures in the London market. The LSE instituted an electronic limit order book in 1997.

[7]In addition, market makers can put quotes on the exchange's electronic screen between 7:30 a.m. and 6:00 p.m. Prior to some Christmas and New Year holidays, the exchange closes by early afternoon.

[8]While the LSE sets specific levels for each stock, this approximation is considered a strong proxy for the NMS level and is typically used by researchers studying the LSE.

1995, with eight hours of trading per day. Settlement procedures in 1995 and since then are very similar to those used on major US stock exchanges. Reporting requirements on the LSE allowed market makers to delay the publication of large trades over 3 NMS for up to 90 minutes and trades over 75 NMS for up to 5 business days.[10] Since few trades exceed 75 NMS, while trades over 3 NMS are frequent, the primary effect of these reporting rules is to delay medium size trades for up to two hours. For the few cases of extremely large block trades, detecting any immediate volatility effects of these trades would be unlikely.

Table 1 presents descriptive statistics across the individual stocks for average share prices, equity capitalization, number of dealers, price volatility, average trade size, number of trades, and other trading activity measures for the 100 largest UK stocks, based on daytime and hourly data. Equity capitalization of the typical FTSE stock is relatively large, ranging from £1.5 billion to £23.5 billion. Studying this sample of stocks is attractive since they are much more likely to have significant numbers of trades of varying sizes than small capitalization stocks. On average, these stocks have 176 trades per day and 22 trades per hour. The institutional nature of the LSE is highlighted by an average trade size of 3.4 million shares valued at £14.1 million and by the fact that less than a quarter of trades are for under one million shares and worth less than £4.7 million.

[9]The number of trades we analyze is the number of trade reports or prints. Trades and trade reports may differ to the extent some trades are bunched together for reporting or some trades are not reported at all.

[10]Board and Sutcliff (1995, 1997) and Gremmill (1996) explore the effects of these reporting rules and question their benefits. Board and Sutcliff (1997) report that in the first half of 1995 for a sample of 10 large and 10 small FTSE-100 stocks that 2.04% and 6.74% of trades respectively had delayed reporting. This strongly suggests that trades of 75 NMS tend to be quite infrequent.

We can also infer that average pound size of one NMS trade is more than £290,000, which greatly exceeds the typical quoted depth on the Nasdaq or NYSE.[11]

Our primary price volatility measure is the absolute value of the closing price minus the opening price, which represents daytime volatility rather than daily volatility. When we move from daytime to hourly data, the mean and standard deviation of stock price volatility drop by more than half. Note that for hourly data, the first trade in the hour is defined as the open and the last trade as the close. This suggests a diversification effect from using hourly data, which has eight times as many observations as daytime data. We also observe that share volume is positively correlated with both the number of trades and average trade size on a daytime (hourly) basis, with correlations of .50 and .52 respectively (.37 and .52 respectively), while the number of trades and average trade size have low negative correlation of -.11 (-.01). It is also noteworthy that these variables exhibit right tailed skewness, with average trade size exhibiting the greatest amount of skewness.

Table 2 presents trading activity statistics at the individual stock level for small, medium and large trade size categories based on a stock's NMS measure. We define small trades as one NMS or less and medium size trades as greater than 1 NMS but less than or equal to 5 NMS and large trades as greater than 5 NMS. Moving from small to large trade sizes, the number of trades falls dramatically, as seen in the daily number of trades mean and quartile statistics reported in Panel A. The correlations of the number of trades across the three size categories are low. It is also not surprising that large trades

[11]This is derived from an average trade size of over 58,000 shares and an average price per share of over £5. The average depth on Nasdaq over this time period is 1000 shares.

have many more missing observations, as indicated by the zeros reported in the first through third quartiles for large trades. It should be noted that small trades in London are similar in market value to medium size trades on the NYSE and Nasdaq.

4. Statistical Methodology

To explore the relation between trading activity and price volatility, we begin by decomposing share volume into its number of trades and average trade size. We then use these two variables as regressors in our model of stock price volatility.[12] As JKL observe, these two trading activity measures have the attractive properties of being weakly correlated with each other, while being strongly positively correlated with share volume. However, the correlations of share volume with average trades size and number of trades is considerably lower for stocks on the LSE, than JKL report for Nasdaq stocks.[13]

In the following analysis, we focus on estimating the price volatility-trading activity relation for each of our 100 FTSE stocks. We use JKL's linear specification in our statistical model:

$$V_{it} = \alpha + \beta A_{it} + \gamma N_{it} + \varepsilon_{it} \qquad (1)$$

where V_{it} represents price volatility, A_{it} represents average trade size and N_{it} represents the number of trades, in each case for stock i over interval t. The equation is estimated from a time series of daytime and/or hourly price volatilities for each of the FTSE-100 stocks. We estimate this equation using Hansen's (1982) generalized method of moments

[12] In section 5, we examine a variety of price volatility and trading activity measures including: average trade size, the number of shares traded, the number of trades and the total market value of these trades for each stock.

[13] This is likely to be due to differences in markets and the different time frames of the data sets.

(GMM) method. In contrast, JKL use a two-step estimation procedure and measure price volatility by the absolute residuals from daily returns regressed against five day-of-the-week dummies and 12 lagged returns to handle the serial correlation in the residuals. The GMM estimation method imposes weak distribution assumptions on the observable variables and endogenously adjusts the estimates to account for general forms of conditional heteroskedasticity and/or serial correlation that may be present in the error structure. Serial correlation in stock price volatility is a particular concern given the widely documented strong positive serial correlation found in squared stock returns.[14]

5. Trading Activity and Stock Price Volatility in the London Market

Table 3 presents summary statistics of the GMM estimates of the price volatility relation with average trade size and trade frequency for individual FTSE stocks. Daytime estimates are presented in the first three columns of Panel A, Table 3. The mean coefficient on the trade frequency is positive and consistently significant, while the coefficient on average trade size is positive, but statistically insignificant.[15] This result holds for the various alternative measures of price volatility: the absolute value of closing price minus opening price, the absolute value of closing price minus opening price measured in natural logs (absolute return) and the absolute value of the error term from a regression of returns on indicators for various seasonal effects. In the third column of estimates, major seasonalities are filtered out of the volatility measure by estimating an

[14]For example, see the survey of GARCH properties in financial claims by Bollerslev, Chou, and Kroner (1992).

[15]The discussion is centers almost exclusively on mean coefficients since median coefficients generally lead to qualitatively similar conclusions.

OLS regression of absolute returns against indicator variables for weekends and holidays, triple witching dates, end-of-the-year and end-of-fiscal-year seasonals.[16] The specific calendar dates for these seasonal indicators are defined in Appendix 1.

The evidence in Panel A is qualitatively similar to the JKL results, though the explanatory power of our model as measured by its adjusted R^2 is much weaker than that found by JKL. Recall that the simple correlations reported in Table 1 of daytime price volatility with the corresponding shares volume, trade frequency and average trade size are all positive, but very low in magnitude (specifically .04, .04 and .01 respectively) in contrast to the corresponding correlations on Nasdaq as reported by JKL. One likely explanation for the widely varying strength of the relation across the two markets is that the London and Nasdaq markets operate under distinctly different rules and regulations and the order flow patterns and number of active investors and dealers is distinctly different in the two markets.

The estimation reported in the last column of Panel A uses close to close price volatility as in JKL. As such, the daily volatility includes an unrelated overnight volatility component. The results show that, on average, neither trade frequency nor average trade size are significant in London.

We further evaluate the robustness of the JKL results for the London market by considering a variety of alternative measures of trade size and trade frequency. This is

[16]Stock return means and conditional variances exhibit seasonalities. Masulis and Ng (1995) document the statistical importance of seasonalities for return means and conditional variances of the FTSE-100 stock index. They confirm the empirical relevance of a Monday, a turn-of-the-year and a turn-of-the-fiscal-year (March 31 for corporations) seasonals. We also include a quarterly triple witching seasonal when exchange traded option and futures contracts on the FTSE-100 expire.

presented in Panel B of Table 3, where the dependent variable is the absolute value of closing price minus opening price for the period. In the first column of figures in Panel B, we replace average (share) trade size with the average market value of trades as the first regressor and continue to use trade frequency as the second regressor. We again find that on average, the regression coefficient for trade frequency is significant. The average adjusted R^2 for the model is .06. In the second column of Panel B, we replace average trade size with total share volume as the first regressor and continue to use trade frequency as the second regressor. We find that when the total volume is included in the regression, rather than just it's components, neither of the regression coefficients is significant on average. This may reflect the high correlation between the two explanatory variables since the adjusted R^2 remains virtually unchanged.

In the third column of Panel B, we replaced average trade size with the log of average trade size and trade frequency with the log of trade frequency as regressors in our model of stock price volatility. Again, we obtain results similar to JKL with only the log trade frequency being significant on average. The regression coefficients on average trade size are significantly positive for 38% of the stocks, and on trade frequency are significantly positive for 76% of the stocks.

Finally, we examine how our inferences change when we use the number of dealers and average trade size per dealer as regressors. If informed investors break up large trades to exploit dealer price guarantees, but continue to trade with dealers offering the best quotes, then we should find that average trade size per dealer is a more informative explanatory variable. The results are presented in the last column of Panel B. We obtain significant t-statistics for 62% of the trade size coefficients and for 63% of the coefficients on the number of active traders. The estimated model has an average adjusted R^2 of .05. This last regression hints at the compatibility of the JKL results with the presence of strategic trading, an issue we examine more carefully in next section. Near the conclusion of the study in Table 6, we test another specific prediction of the hypothesis that some investors are acting strategically to exploit the guaranteed maximum quoted depth in the market.

6. Evidence of Stealth Trading and Its Impact on Stock Price Volatility

This section examines whether our earlier daytime evidence, which parallels the JKL results is also consistent with the Barclay and Warner results on stealth trading. The use of daytime data may attenuate the influence of average trade size on stock price volatility because of the smoothing that time aggregation can produce. However, avoiding time aggregation altogether is not a viable solution, since use of individual transactions would render the trade frequency variable uninformative. We strike a balance between these considerations by studying hourly price volatility and trading activity.

In Table 4, we report estimates based on the more frequently sampled hourly data. In Panel A, the regressors are left unchanged, but alternative measures of stock price volatility are used. The qualitative results are very similar to the prior table with two major differences. While average trade size continues to be insignificant on average, the mean t-statistic is about 40% larger. Second, the adjusted R^2 implies that the model explains 3 to 4% less of the hourly price volatility than it does for daytime price volatility. This is not surprising given the relatively larger impacts and frequency of bid-ask bounce and noise trading effects on hourly volatility. These effects tend to be partially diversified away when using daytime or longer observation periods.

We next consider the effects of using alternative regressors. In the first column of Panel B, the explanatory variables are trade frequency and average market value of trades, which replaces average (share) trade size. We find that only trade frequency is statistically significant. In the second column of Panel B, the explanatory variables are trade frequency and total share volume (in place of average trade size). Again, only the coefficient on trade frequency is significant. However, in both of these experiments, the trade size variable has a mean t-statistic that is close to significant and in nearly half of the sample, they are significant at the 10% level. Although this evidence appears to generally support the JKL conclusions that trade frequency has a more dominant effect on price volatility, the use of hourly data strengthens the importance of trade size. In addition, trade size significantly impacts price volatility for nearly half the stocks in the FTSE 100.

In the third column of panel B, the explanatory variables are the log of trade frequency and the log of average trade size. On average, both regression coefficients are positive and significant, with 62% of the coefficients on average trade size and 86% of the coefficients on trade frequency being significant. This is further evidence that use of hourly data increases the power of the average trade size variable to affect stock price volatility.

In the last column of Panel B, we examine how our inferences change when the explanatory variables are the number of dealers and average trade size per dealer. Average trade size per dealer should capture the effect of multiple trades by an investor who breaks up a large trade to exploit a dealer's guaranteed quoted depth. This follows because investors have the incentive to continue trading with the dealer offering the best quotes. In Table 3, we find that the mean coefficient on average trade size per dealer is significant for daytime data. The results in Table 4 shows that this is the case with hourly data as well.

In summary, a comparison of daytime and hourly evidence in Tables 3 and 4 reveals that mean t-statistics tend to rise with the use of hourly data for the trading activity variables. Perhaps, more importantly, the coefficients on the trade size variable are statistically significant almost as frequently as the coefficients on trade frequency. This suggests that the number of trades is not a sufficient trading activity statistic, at least as it pertains to stock price volatility. The evidence is consistent with less time aggregated hourly data being more informative about the price volatility process.[17] The evidence also suggests that stealth trading or liquidity motives can be causes of stock price volatility.

Of the mean t-statistics shown in Table 4, the regressions based on open to close price volatility with average trade size and trade frequency are the smallest. In the remainder of the paper, we focus on this specification so as to bias our analysis against the stealth trading and liquidity hypotheses. It is also important to recognize that there is some bias against trade size being influential due to delayed reporting of some trades over 3 NMS for up to two hours and for very large trades over 75 NMS for up to 5 trading days. The frequency of two-hour delays is much higher due to LSE trading

[17]In addition, the hourly regressions have many more degrees of freedom, which tends to reduce the estimated standard errors.

patterns, so we are especially concerned with its impact. Therefore, we repeat our estimations of volatility and trading activity variables reported in the paper by including lagged trading activity variables for both daytime and hourly data. We found no statistical significance for the lagged variables.[18]

The analysis of Tables 3 and 4 is based on means of all the stocks in the FTSE 100 index. It leaves open the possibility that the evidence may differ substantially for stocks separated into equity capitalization portfolios, as reported by JKL. A key question in this analysis is whether aggregating individual stocks into equity capitalization quartiles lowers the noise in the price volatility-trading activity relation or reduces the power of the test by minimizing the cross sectional variability in the variables. JKL report that the relation varies across equity capitalization categories, that average trade size has a positive and statistically significant effect on price volatility for some equity capitalization categories, though the number of trades continues to be more important economically and statistically.

To examine whether the trading activity-price volatility relation is invariant to different equity capitalization categories, we break our sample into equity capitalization quartiles based on prior year-end market values. We also examine GMM estimates for individual stocks averaged by equity capitalization quartiles.[19] The daytime and hourly results are both similar to those reported in Tables 3 and 4. Interestingly, when we use hourly data, we find that the mean coefficient on average trade size is positive and statistically significant for the two largest equity capitalization categories. The evidence

[18]These regressions are available from us upon request.

also indicates that average trade size can be more informative in the London market when hourly data are used rather than the daytime evidence.

6.1 Detailed Analysis of Small Trade Effects

We next investigate whether the price volatility-trading activity relation is fundamentally different across trade size categories due to different concentrations of liquidity motivated or information motivated trading. In particular, does this relation hold for trades above and below the maximum guaranteed depth of existing quotes? We hypothesize different price volatility-trading activity relations across trade size categories if traders strategically break up their orders to obtain better price execution or dealers offset block trades via smaller trades in the inter-dealer market.

In Table 5, we decompose trades into small, medium and large size categories. This permits us to investigate whether the trading activity variables have consistent effects on price volatility across disparate trade size categories. We uncover the striking result that both trading activity variables have statistically insignificant coefficients in the case of medium and large trades and that this holds for both the daytime and hourly data. At the same time, the mean t-statistics on the number of trades and average trade size for the small trade category are positive and significant using hourly data and they are significant at the 10% level for more than a third of the stocks based on daytime data. These results are also qualitatively similar when we combine the medium and large trade categories. This evidence is consistent with the small trade size category capturing a substantial proportion of the strategic trading activity, which in turn has a strong effect on

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[19]To conserve space, several of these robustness checks are not reported here, but are presented in our earlier working paper.

price volatility in the London market. However, it is important to recognize that there are several alternative explanations for why small trades can have a large impact on price volatility, which are discussed below.

Next, using both daytime and hourly data, we categorize each individual trade into one of three trade size categories and estimate the model for each stock in the FTSE 100 three times, once for trades in each of the three size categories. This is equivalent to interacting the two trading activity variables (and the intercept) with a set of indicator variables that takes on value of one when the trade is in a particular size category, and is zero otherwise. Because large trades occur infrequently, we combine the medium and large trades categories. As expected, the mean coefficients on trade frequency and average trade size are significant for small trades. In addition, the mean coefficient on average trade size is larger and on trade frequency is smaller, for the small trade category compared to the larger trade categories. These results suggest that the price volatility-trading activity relation found by JKL does not hold for trades of one NMS or less. Furthermore, the medium and large trade regression results show that when small trade activity variables are excluded, the mean coefficient on trade frequency becomes significant. However, based on the evidence in Table 5, these results are spurious and are due to an omitted variable bias created by the exclusion of the small trade activity measures from the equation. Given these empirical results, we focus our investigation on the small trade category in the following analysis.

To explore the small trade evidence further, we censor our trading activity data by calculating trade frequency and average trade size based solely on trades of one NMS or less (small trades). It is important to realize that the range of trade sizes in this sample varies stock by stock, with larger size trades included in the small size category, if that stock typically has larger trades (and thus, has a larger NMS). It is also important to recognize the structural effects. Specifically, dealers accommodating customers demands to trade large blocks can trigger a number of small inter-dealer purchases prior to a large sale to a customer and a number of small inter-dealer sales following a large purchase from a customer, as the initial dealer re-adjusts its inventory position following the block trade. The London market also makes stealth trading difficult in that there are a small number of dominant market makers and a small number of large institutional traders. This make anonymity difficult to obtain and if the market maker perceives that an institutional investor is misleading them, the dealer has the opportunity in the future to give them poorer executions on large trades.[20]

We examine stocks sorted into equity capitalization quartiles to evaluate whether the small trade category is a proxy for firm size. If it is, then we should find different results across the equity capitalization quartiles. On the other hand, under the stealth trading or liquidity hypotheses, stocks in all equity capitalization categories should be impacted similarly. Thus, this aggregation procedure also enables us to evaluate the effect of equity capitalization, while controlling for extremes in trade size.

When the basic regression equation is re-estimated with the censored trade size sample, we find that in all equity capitalization portfolios, both trade frequency and average trading size have median t-values that are significant at the 10% level for daytime volatility and have mean and median t-values which are significant at the 5%

[20]There are also anecdotal stories of traders who combine their trades into blocks because they felt they would get better fills.

level for hourly volatility. All the mean coefficients are positive, which indicates that both larger size trades and more trades within the small size category increase price volatility.[21] We also observe in the hourly data that as we go from smallest to largest equity capitalization portfolios, the effect of trade size strengthens, while the effect of trade frequency weakens. A similar pattern is observed for number of trades using daytime data. This evidence further supports the conclusion that informed trading, which is concentrated in "small" trades, affects price volatility through both average trade size and trade frequency. Finally, the evidence in this table shows that our small trade effect is robust across equity capitalization classes, which is consistent with a stealth trading effect.

We now investigate whether the small trade size effect is observed across active and inactive stocks. This analysis addresses the question of whether informed traders have more of a tendency to break up their order flows into smaller size trades for less frequently traded stocks. Highly active stocks with sufficient liquidity may reduce the need for informed traders to hide among small trades. A limitation of this portion of our analysis is that FTSE 100 stocks are some of the most liquid stocks in U.K. Still, as shown in Table 1, there is quite a dispersion in trading frequency among the 100 stocks. For example, the mean daily market volume is £14 million with a standard deviation of £17 million. This analysis also allows us to assess whether small trades are proxying for the market value of trades.

[21]With the exception of the largest equity capitalization portfolio in the daytime volatility regression, all the parameter estimates are significant. But even for the exception, the median t is significant.

We evaluate how the price volatility relation exhibited by small trades varies across active and inactive stocks by grouping stocks into equity capitalization quartiles based on the December 1994 annual pound volume. We examine the mean GMM coefficient estimates of individual stocks for each pound value quartile using both daytime and hourly data. The mean coefficients for both the number of trades and average trade size are significantly positive, except for the smallest daytime quartile. For the smallest quartile, only the mean coefficient on trade frequency is significant, even though almost 50% of the stocks have significant coefficients for average trade size. These results indicate that the small trade variable is not proxying for stocks' market volume. For the hourly results, we also find that the mean coefficient estimate for average trade size tends to rise as we go from smallest to largest equity capitalization quartile. This suggests that informed trading is more pronounced in the small trade category for stocks with higher trading volume.

An alternative explanation for the significance of the small trades is that market makers reduce quoted depth when volatile market conditions occur. Under this liquidity supply explanation, the causation is reversed. This could be the primary relation between the variables or it could represent a feedback effect. To examine the importance of this alternative explanation, we conduct causality tests by regressing each of the three variables (volatility, trade size and number of trades) on their own lags and the lags of the other variables. There is no evidence from daytime data that lagged volatility has power to predict trade size or number of trades. With hourly data, the first lag of volatility in 58 (out of 100) firms is significant at the 10% level in predicting the number of trades. Thus, there is limited evidence of a feedback effect at the hourly level, but not at the daytime level. This evidence also indicates that delayed reporting of trades over 3 NMS is not especially important at an hourly level.

6.2 Analysis by Trade Size Within the Small Trade Category

In Table 6, we break the small trade size sample in two. We sort the data based on whether a trade is under one half NMS or is greater. It should be remembered that the market value of one NMS trade averages £300,000, which translated into dollars would be classified as a medium size or large block trade in New York. Some further analysis of small trades seems appropriate, given our informed trading hypothesis. We expect to see information traders preferring to trade at a full NMS, since this is the largest trade size on which they are guaranteed execution at the stated quotes. Larger trades would allow the dealer to adjust the quotes in reaction to any market orders to buy or sell. Smaller trades would not be as useful in exploiting private information, since they tend to involve relatively higher percentage transaction costs. Thus, we expect to find that larger orders in this category are more strongly associated with information-based trading. As such, we expect that trade size is likely to have a more discernible impact on stock prices and price volatility for the relatively larger trades in the small trade category. However, it is also possible for some of these orders close to one NMS to represent inter-dealer trades following a block trade that may or may not be reported at that time. As such, this type of small order can be capturing much of the information content in the block trade itself, much like front running a large order could.

Examining Table 6, we find for daytime data that only relatively larger trades exhibit a significant relation between price volatility and the trading activity variables, with only trade frequency being significant. However, hourly data potentially increases the influence that average trade size exerts on price volatility. We find that for trades closer to one NMS, hourly price volatility is significantly positively impacted by both trade size as well as trade frequency. In contrast, for relatively smaller trades neither trading activity variable is significant. This is consistent with these relatively small trades being liquidity or noise motivated. Thus, we find evidence in Table 6 consistent with information motivated trading having a stronger impact on price volatility as the size of trades nears one NMS and being weaker for smaller trades. This reinforces our earlier evidence in Panel B of Table 3, which showed that the coefficient on average trade size per dealer is significant in impacting stock price volatility. The evidence is consistent with informed investors breaking up large trades to exploit dealers' guaranteed maximum depth. It is also consistent with dealers executing trades around 1 NMS in the inter-dealer market subsequent to a large block purchase or prior to a large block sale with a customer.

7. Summary and Conclusions

In this study, we examine the generality of the Jones, Kaul, and Lipson (1994) conclusion that stock price volatility is strongly impacted by trade frequency (the number of trades), but not by trade size. By studying the price volatility of stocks in the FTSE 100 index, the major stock index in London, we develop evidence that allows us to make an independent evaluation of the importance of trade frequency. For our overall sample, price volatility on the London Stock Exchange is directly related to trade frequency and more weakly, but positively related to trade size. In this regard, we support the general conclusion of Jones, Kaul, and Lipson.

We also investigate whether the results observed for the London market are consistent with strategic trading by information motivated investors or liquidity traders seeking to exploit the guaranteed maximum quoted depth. For this purpose, we first aggregate transactions data to an hourly basis to preserve the magnitude of large trades in the average trade size variable. Second, we classify trading activity measures by trade size categories to better detect the effects of traders who act strategically by breaking up large blocks into a number of smaller trades. We find that trades in the small category are the only ones that consistently have a significant impact on price volatility. For small trades, we also find significant impacts on price volatility from both trade size and trade frequency, particularly when we move from daytime to hourly data. In examining whether this relation varies across stocks categorized by equity capitalization or trading volume, we find no evidence of significant differences, which indicates that trade size is not acting as a proxy for equity capitalization or stock liquidity.

An important finding of the study is that the impact on price volatility of trading activity is concentrated in trades close to one *normal market size*. This evidence is consistent with strategic trading behavior of informed investors being concentrated in orders of a particular size. Informed traders have incentives to purposely break up large block trades so as to execute trades at the existing quotes. Trades of one *normal market size* accomplish this objective. Trades of one *normal market size* can also be attractive to large liquidity traders, who break up their trades seeking execution at guaranteed quote levels or to dealers adjusting their inventory position following large block trades.

The evidence that small trades have a strong influence on prices is also consistent with the empirical evidence of Barclay and Warner (1993), who study trading on the

NYSE and find that medium size trades (defined as trades of 1,000 to 10,000 shares) have greater price impacts than large trades. Given that small trades on London Stock Exchange are closer in market values to medium size trades on NYSE, the two studies draw consistent conclusions as to which trade sizes have the most influence on stock prices and price volatility. Our evidence suggests that break ups of blocks by informed traders is a likely explanation for he significant impact of smaller traders in the London market. We conclude that stealth or informed trading and break-ups of large trades by investors seeking liquidity or dealers adjusting their inventory positions are the most likely explanations for the Jones, Kaul, and Lipson result that the number of trades appears to be a sufficient statistic for trading activity’s effect on stock price volatility, at least insofar as it pertains to the London Stock Exchange.

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References

Amati, A., Pffeiderer, P., 1988. A Theory of Intraday Trading Patterns: Volume and Price Variability. Review of Financial Studies 1, 3-40.

Andersen, T., 1996. Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility. Journal of Finance 51, 169-204.

Back, K., 1992. Insider Trading in Continuous Time. Review of Financial Studies 5, 387-410.

Barclay, M., Warner, J., 1993. Stealth Trading and Volatility: Which Trades Move Prices. Journal of Financial Economics 34, 281-305.

Blume, L., Easley, D., O’Hara, M.,1994. Market Statistics and Technical Analysis: The Role of Volume. Journal of Finance 49, 153-182.

Board, J., Sutcliffe, C., 1995. The Effects of Trade Transparency in the London Stock Exchange: A Summary. London School of Economics Working Paper.

Board, J., Sutcliffe, C., 1997. The Proof of the Pudding: The Effects of Increased Trade Transparency in the London Stock Exchange. London School of Economics Working Paper.

Bollerslev, T., Chou, R., Kroner, K., 1992. ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence. Annals of the Journal of Econometrics, 52, 5-60.

Claessens, S., Dasgupta S., Glen, J., 1998. The Cross Section of Stock Returns: Evidence from Emerging Markets. Emerging Markets Quarterly 2, 4-13.

Datar, V., Naik, N., Radcliffe, R., 1998. Liquidity and Stock Returns: An Alternative Test. Journal of Financial Intermediation 203-219.

Easley, D., O'Hara, M., 1987. Price, Trade Size, and Information in Securities Markets. Journal of Financial Economics 19, 69-90.

Foster, D., Vishwanathan, S., 1990. A Theory of Intraday Variations in Volume, Variance, and Trading Costs in Security Markets. Review of Financial Studies 3, 593-624.

Foster, D., Vishwanathan, S., 1995. Can Explain the Volume-Volatility Relation? Journal of Business and Economic Statistics 13, 379-396.

Gallant, A., Rossi, P., Tauchen, G., 1992. Stock Prices and Volume. Review of Financial Studies 5, 199-242.

Glosten, L., Milgrom, P., 1985. Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. Journal of Financial Economics 13, 71-100.

Gemmill, G., 1996. Transparency and Liquidity: A Study of Block Trades on the London Stock Exchange under Different Publication Rules. Journal of Finance 51, 1765-1790.

Hansen, L., 1982. Large Sample Properties of Generalized Method of Moments Estimators. Econometrica 50, 1029-54.

Hu, Shing-yang, 1997. Trading Turnover and Expected Stock Returns: The Trading Frequency Hypothesis and Evidence from the Tokyo Stock Exchange. University of Chicago Working Paper.

Huang, R., Stoll, H., 1991. Major World Equity Markets: Current Structure and Prospects for Change. Monograph Series in Finance and Economics 1991-1993.

Jain, P., Joh, G., 1988. The Dependence between Hourly Prices and Trading Volume. Journal of Financial and Quantitative Analysis 23, 269-284.

Jones, C., Kaul, G., Lipson, M., 1994. Transactions, Volume and Volatility. Review of Financial Studies 7, 631-651.

Karpoff, J., 1987. The Relation between Price Changes and Trading Volume: A Survey. Journal of Financial and Quantitative Analysis 22, 109-126.

Kaul, G., Nimalendran, M., 1990. Price Reversals: Bid-Ask Errors or Market Overreaction? Journal of Financial Economics 28, 67-93.

Kyle, A., 1985. Continuous Auctions and Insider Trading. Econometrica 53, 1315-1336.

Lakonishok, J., Lev, B., 1987. Stock Splits and Stock Dividends: Why, Who, and When. Journal of Finance 42, 913-932.

Lamoureux, C., Lastrapes,W., 1990. Heteroscedasticity in Stock Return Data: Volume Versus GARCH Effects. Journal of Finance 45, 221-229.

Lang, L., Litzenberger, R., Madrigal, V., 1992. Testing Financial Market Equilibrium under Asymmetric Information. Journal of Political Economy 100, 317-348.

Lo, A. W., MacKinlay, A. C., 1990. An Econometric Analysis of Nonsyncronous Trading. Journal of Econometrics 45 181-211.

Lo, A., Wang, J., 2000. Trading Volume: Definitions, Data Analysis and Implications for Portfolio Theory. Review of Financial Studies 13, 257-300.

Masulis, R., Ng, V., 1995. Overnight and Daytime Stock-Return Dynamics on the London Stock Exchange: The Impacts of 'Big Bang' and the 1987 Stock-Market Crash. Journal of Business and Economic Statistics 13, 365-378.

Newey, W., West, K., 1987. A Simple Positive Semi-definite Heteroscedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703-08.

Reiss, P., Werner, I., 1996. Transacting Costs in Multiple Dealer Markets: Evidence from the London Stock Exchange, in: A. Lo ed. The Industrial Organization and Regulation of the Securities Industry. University of Chicago Press, 125-176.

Schwartz, R., 1991. The Reshaping Equity Markets. New York: Harper-Collins.

Schwert, G. W., 1989. Why Does Stock Volatility Change Over Time. Journal of Finance 44, 1115-1154.

Table 1

Stock Descriptive Statistics

The table presents descriptive statistics of daytime and hourly price volatility and trading activity for FTSE 100 stocks in year 1995. Returns are calculated from closing prices minus opening prices measured in natural logs. |Close-Open| and |Return| are multiplied by 100. Average trade size is defined as share volume divided by number of trades, where trades are for buy transactions. Equity capitalization is measured at 1994 year-end prices and is in millions of pound sterling. Share volume, pound volume and average trade size are reported in thousands. In Panel D, daytime correlations are in the upper triangle of the correlation matrix and hourly correlations are in the lower triangle.

	Mean	Std. Dev.	Min.	1^{st} Quartile	Median	3^{rd} Quartile	Max.
Panel A: Firm Sample (100 stocks)							
Daytime Price (£)	5.14	2.59	0.6	3.31	4.71	6.34	16.63
Equity Cap. (£)	4967	4686	1455	2036	2994	6170	23522
No. of Dealers	16.5	2.5	7	15	17	18	20
NMS	58280	40989	3000	25000	50000	100000	200000
Panel B: Daytime Sample (23969 observations)							
|Close-Open|	4.947	12.916	0	1	3	6	830
|Return|	1.070	2.651	0	0.295	0.639	1	205
Share Volume	3369	4304	0.094	1011	2076	4131	93895
Mkt. Volume (£)	14121	17195	0.910	4703	9379	17633	595039
Ave. Trade Size	22	25	0.072	9	16	26	1040
No. of Trades	176	182	1	76	126	214	3057
Panel C: Hourly Sample (188631 observations)							
|Close-Open|	2.020	6.180	0	0	1	3	833
|Return|	0.435	1.328	0	0	0.297	0.575	204
Share Volume	428	990	0.001	37	159	475	85231
Mkt. Volume (£)	1794	3950	0.004	170	728	2090	393426
Ave. Trade Size	20	46	0.001	3	10	23	9390
No. of Trades	22	25	1	8	15	28	1514

Panel D: Correlation Matrix

	|Close-Open|	|Return|	Share Volume	£ Volume	Ave. Tr. Size	No. of Trades
|Close-Open|	1	.857	.042	.133	.013	.042
|Return|	.894	1	.108	.088	.069	.050
Share Volume	.024	.057	1	.780	.522	.495
Mkt. Volume (£)	.065	.046	.842	1	.310	.528
Ave. Trade Size	.013	.039	.524	.421	1	-.108
No. of Trades	.022	.023	.370	.394	-.013	1

Table 2
Descriptive Statistics by Trade Size Categories

The table presents descriptive statistics of FTSE 100 stocks in 1995 categorized by trade size. Trades are categorized as small if the trade size ≤ 1 normal market size (NMS), medium if 1 NMS < trade size ≤ 5 NMS, and large if trade size > 5 NMS. Average trade size (ATS) is defined as buy share volume divided by (NT), the number of buy trades. Average trade size numbers are reported in thousands. In Panel C, the daytime correlations are in the upper triangle of the correlation matrix and the hourly correlations are in the lower triangle. The numbers in parentheses are p-values.

	No. of Obs.	Mean	Std. Dev.	Min.	1st Quartile	Median	3rd Quartile	Max.
				Panel A: Daytime Sample				
Small ATS	23967	7	5	.030	3	5	9	50
Med. ATS	23148	140	95	3.100	71	116	183	1000
Large ATS	12975	568	636	16.800	250	394	660	9390
Small NT	23969	165	178	0	68	115	200	3024
Med. NT	23969	10	9	0	4	8	13	354
Large NT	23969	1	2	0	0	1	2	118
				Panel B: Hourly Sample				
Small ATS	187694	6	7	.001	2	4	8	100
Med. ATS	93422	142	110	3.014	70	103	184	1000
Large ATS	23117	548	650	15.700	236	353	610	9390
Small NT	188631	21	25	0	7	14	26	1514
Med. NT	188631	1	2	0	0	0	2	112
Large NT	188631	0	1	0	0	0	0	60

Panel C: Correlation Matrix

	Small ATS	Med. ATS	Large ATS	Small NT	Med. NT	Large NT
Small ATS	1.000	.479	.346	-.055	.129	.019
Med. ATS	.336	1.000	.583	.376	.007**	-.103**
Large ATS	.257	.514	1.000	.259	.024	.008
Small NT	.017	.284	.218	1.000	.320	.057
Med. NT	.179	-.008*	-.002**	.259	1.000	.537
Large NT	.058	-.040	.052	.071	.346	1.000

* denotes the value is *not* significant at the 5% level.
** denotes the value is *not* significant at the 10% level.

Table 3
Regressions of Various Daytime Price Volatility and Trading Activity Measures

The following equation is estimated by GMM for each individual FTSE 100 stock over 1995

$$V_{it} = \alpha + \beta A_{it} + \gamma N_{it} + \varepsilon_{it}$$

where V_{it} is the volatility measure for stock i at interval t, A is the average trade size and N is the number of trades. In Panel A, A is defined as buy share volume divided by N, the number of buy trades. Volatility is alternatively measured as absolute value of closing price minus opening price (Open to Close), absolute value of closing price minus opening price measured in natural logs (Return), absolute value of the error term from an OLS regression of return on indicator variables for turn of the year, end of tax year, triple witching days, and first trading day following weekends and holidays (Filtered Return), and absolute value of closing price minus lagged closing price (Close to Close). In the filtered regression both average trade size and number of trades are adjusted for seasonalities. In Panel B, volatility is measured by the absolute value of closing price minus opening price and the regressions are performed for alternative measures of average trade size and number of trades. The table reports the means for the estimated coefficients and t statistics, the percentage of p-values of positive t statistics that are less than 0.1, and the mean $\overline{R}^2$.

	A: Alternative Price Volatility Measures			
	Open to Close	Return	Filtered Return	Close to Close
A_{it}				
Mean coeff.	6.827E-07	1.213E-07	1.189E-07	1.905E-07
Mean t-stat.	.98	1.12	1.11	.38
% p-val(t) < .1	28	33	29	18
N_{it}				
Mean coeff.	1.799E-04	3.790E-05	3.660E-05	3.558E-05
Mean t-stat.	2.37	2.30	2.24	.66
% p-val(t) < .1	68	67	67	23
Mean $\overline{R}^2$	.06	.06	.05	.02

	B: Alternative Trading Activity Measures			
	Pound Ave. Trade Size & No. of Trades	Share Volume & No. of Trades	Log Ave. Trade Size & Log No. of Trades	Trade Size Per Dealer & No. of Dealers
A_{it}				
mean coeff.	1.056E-07	7.410E-09	9.337E-03	1.127E-07
mean t-stat.	1.01	1.12	1.16	2.10
% p-val(t) < .1	29	32	38	62
N_{it}				
mean coeff.	1.811E-04	6.377E-05	2.945E-02	8.114E-04
mean t-stat.	2.37	1.50	2.25	1.92
% p-val(t) < .1	69	46	76	63
Mean $\overline{R}^2$	0.06	0.06	0.05	0.05

Table 4

Regressions with Alternative Measures of Hourly Price Volatility and Trading Activity

GMM estimation is performed for each FTSE 100 stock. The basic regression estimated is

$$V_{it} = \alpha + \beta A_{it} + \gamma N_{it} + \varepsilon_{it}$$

where V_{it} is the volatility measure for stock i at interval t, A is the average trade size and N is the number of trades. In Panel A, A is defined as buy share volume divided by N, the number of buy trades. Volatility is alternatively measured as absolute value of closing price minus opening price (Open to Close), absolute value of the natural log of closing price minus the natural log of opening price (Return), and absolute value of the error term from a regression of return on indicator variables for turn of the year, end of tax year, triple witching days, and first trading day following weekends and holidays (Filtered Return). In the filtered regression both average trade size and number of trades are adjusted for seasonalities. In Panel B, volatility is measured as absolute value of the closing price minus the opening price and the regressions employ alternative measures of average trade size and number of trades. The table reports the means of the estimated coefficients and t statistics, the percentage of p-values of positive t statistics less than 0.1, and the mean $\overline{R}^2$.

	A: Alternative Price Volatility Measures		
	Open to Close	Return	Filtered Return
A_{it}			
mean coeff.	8.535E-08	1.814E-08	1.763E-08
mean t-stat.	1.44	1.57	1.56
% p-val(t) < .1	45	45	46
N_{it}			
mean coeff.	6.114E-04	1.093E-04	1.056E-04
mean t-stat.	3.24	3.15	3.12
% p-val(t) < .1	87	85	84
Mean $\overline{R}^2$	.02	.02	.02

	B: Alternative Trading Activity Measures			
	Pound Ave. Trade Size & No. of Trades	Share Volume & No. of Trades	Log Ave. Trade Size & Log No. of Trades	Trade Size Per Dealer & No. of Dealers
A_{it}				
mean coeff.	1.507E-08	4.422E-09	1.577E-03	3.506E-08
mean t-stat.	1.51	1.57	2.18	2.16
% p-val(t) < .1	44	49	62	61
N_{it}				
mean coeff.	6.132E-04	5.297E-04	6.257E-03	1.341E-03
mean t-stat.	3.25	2.41	3.72	3.72
% p-val(t) < .1	87	67	86	85
Mean $\overline{R}^2$	0.02	0.02	0.02	0.02

Table 5
Regressions of Price Volatility on Average Trade Size and Number of Transactions for Different Trade Sizes

The regression estimated is

$$V_{it} = \alpha + \beta_j \sum_j A_{it}^j + \gamma_j \sum_j N_{it}^j + \varepsilon_{it}$$

where V_{it} is volatility defined as the absolute value of closing price minus opening price for stock i at interval t, A^j is average trade size for trade category *j*, defined as its buy share volume divided by N^j, its number of buy trades, where trade categories are small, medium, large, or medium plus large. A trade is defined as small if it is ≤ 1 NMS (normal market size), medium size if 1 NMS < trade size ≤ 5 NMS and large if trade size > 5 NMS. GMM estimation is performed individually for each FTSE 100 stock over 1995. The table reports means of estimated coefficients and t statistics, as well as percentages of p-values for positive t statistics less than 0.1.

	Daytime	Hourly	Daytime	Hourly
A_{it}	Small	Small	Small	Small
mean coeff.	5.217E-06	4.936E-07	4.313E-06	5.177E-07
mean t-stat.	1.24	2.06	1.25	2.09
% p-val(t) < .1	36	64	41	68
N_{it}	Small	Small	Small	Small
mean coeff.	9.392E-05	5.550E-04	8.709E-05	5.653E-04
mean t-stat.	1.50	2.25	1.52	2.25
% p-val(t) < .1	43	65	44	66
A_{it}	Medium	Medium	Medium+Large	Medium+Large
mean coeff.	8.641E-08	1.272E-08	1.720E-08	8.527E-09
mean t-stat.	-0.09	0.21	0.00	0.37
% p-val(t) < .1	5	12	8	15
N_{it}	Medium	Medium	Medium+Large	Medium+Large
mean coeff.	5.164E-04	1.156E-03	9.029E-04	1.204E-03
mean t-stat.	0.80	1.27	0.95	1.63
% p-val(t) < .1	26	33	26	44
A_{it}	Large	Large		
mean coeff.	-9.093E-10	7.741E-09		
mean t-stat.	-0.06	0.39		
% p-val(t) < .1	4	8		
N_{it}	Large	Large		
mean coeff.	2.277E-03	1.090E-03		
mean t-stat.	0.09	-0.18		
% p-val(t) < .1	5	1		
Mean $\bar{R}^2$	0.08	0.03	0.07	0.03

Table 6
Regressions of Price Volatility on Average Trade Size and Number of Transactions
for Small Trade Size Category

The estimated regression equation is

$$V_{it}^{j} = \alpha + \beta A_{it}^{j} + \gamma N_{it}^{j} + \varepsilon_{it}^{j}$$

where V_{it}^{j} is the volatility measured as the absolute value of closing price minus opening price for stock i at interval t and trade size category j, *A* is the average trade size defined as buy share volume divided by number of buy trades, and *N* is the number of buy trades. GMM estimation over 1995 is performed for each FTSE 100 stock where small trades defined as share volume ≤ 1 NMS (normal market size). The table reports means of estimated coefficients and t statistics as well as the percentage of p-values of positive t statistics less than .1.

	Daytime Price Volatility		Hourly Price Volatility	
	Below Median Share Volume	Above Median Share Volume	Below Median Share Volume	Above Median Share Volume
A_{it}				
mean coeff.	2.961E-06	7.436E-06	2.847E-07	6.470E-07
mean t-stat.	.63	1.25	.51	1.76
% p-val(t) < .1	16	38	17	58
N_{it}				
mean coeff.	-2.463E-04	2.776E-04	6.772E-04	5.682E-04
mean t-stat.	.53	1.89	1.09	2.31
% p-val(t) < .1	14	51	33	66
Mean $\overline{R}^2$	.01	.06	.01	.02