THE BID-ASK SPREAD ON STOCK INDEX OPTIONS: AN ORDERED PROBIT ANALYSIS

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INTRODUCTION

This article uses high frequency intraday data to examine the determinants of the bid–ask spread on stock index options traded at the London International Financial Futures and Options Exchange (LIFFE), an open outcry market with competing price makers. An ordered probit methodology is used to reflect the limited number of alternative integer values taken by the bid–ask spread (see Bollerslev and Melvin, 1994), and three alternative measures of price risk in the options market are compared, namely via exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models of options price volatility and underlying volatility, and an option-implied volatility estimate.

There has been extensive theoretical research into the determinants of the bid–ask spread, but empirical work has been more limited. The

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theory highlights the importance of price risk (e.g., Ho and Stoll, 1983), trading activity (e.g., Copeland and Galai, 1983; Lee, Mucklow, and Ready, 1993), and competition (e.g., McInish and Wood, 1992) as influential factors in the determination of bid–ask spreads. Price risk in the form of high volatility increases inventory risk for dealers, and is regarded as an indirect measure of informed trading, and thus should induce wider spreads. In the case of options, price risk could derive from options market volatility and/or underlying volatility. High levels of trading activity are hypothesized to coincide with narrow spreads because market makers are able to turn their inventories faster and thus reduce both risk and capital requirements.

In addition, market structure is important: A higher level of competition among market makers should reduce spreads, and the intraday behavior of spreads can be affected by the type of market structure. Chan, Chung, and Johnson (1995b) compare the influence of the differing market structures of the Chicago Board Options Exchange (CBOE) and the New York Stock Exchange (NYSE) on the intraday behavior of spreads. In contrast to a U-shaped intraday pattern in spreads reported for specialist markets, they report narrow spreads near the close in the CBOE and suggest that this reflects inventory control in markets with competing market makers. The LIFFE index options market consists of competing market makers; therefore, the behavior of spreads near the open and close is expected to resemble the CBOE.

Previous studies have focused on other markets [e.g., McInish and Wood (1992) for NYSE stocks and Bollerslev and Melvin (1994) for the foreign exchange market] or have been largely descriptive [e.g., Chan et al. (1995b) for CBOE options on individual stocks]. This article extends the literature by examining a stock index option within an ordered probit framework, using three distinct measures of price volatility. By using options market data, an additional contribution is made by examining underlying market volatility as a measure of price risk.

The bid–ask spread for stock index options traded at LIFFE is found to be

1. Insignificantly related to options market volatility
2. Directly related to both the instantaneous and expected price volatility of the underlying stock market index
3. Inversely related to current trading activity in the market
4. Wide in the opening period of the trading day and narrow near the close

The first finding represents new evidence on options market microstructure and is robust across a range of different model specifications. Underlying market volatility is a key determinant of options prices, but previous work has not highlighted such an influence on spreads, especially compared to options market volatility.

The other findings generally support theoretical predictions, e.g., Foster and Viswanathan's (1990) model is supported in the observation of narrow spreads when volume is high and prices are less volatile, in contrast to the Admati and Pfleiderer (1988) prediction of narrow spreads when volume is high and prices are more volatile.

MARKET MICROSTRUCTURE THEORY ON BID–ASK SPREADS

The market microstructure literature (e.g., O'Hara, 1995; Chan et al., 1995b) considers the following three approaches to explaining the behavior of bid–ask spreads: market structure, inventory control, and information asymmetry.

Market Structure

A clear theoretical and empirical distinction exists between the intraday behavior of bid–ask spreads in markets with a monopolistic specialist (e.g., NYSE) and those with competing market makers [e.g., National Association of Securities Dealers Automated Quotation (NASDAQ)]. Brock and Kleidon (1992) developed a model where a single specialist has monopolistic power and is faced with inelastic transactions demand at the open and close of trading due to the overnight accumulation of information prior to opening and the immediacy of the nontrading period after the close. The specialist can price discriminate during these crucial periods and can extract monopolistic profits, particularly if he has access to any opening order imbalances. Consequently, with a market served by a single specialist, wide bid–ask spreads are expected near the open and close of trading. In contrast, in markets with competing market makers one would not expect to observe the U-shaped intraday pattern if the specialist's monopolistic power is an important influence on such behavior.

Brock and Kleidon (1992), McInish and Wood (1992), Lee et al. (1993), and Chan et al. (1995b) show that the spreads at the NYSE follow a U-shaped pattern throughout the day. In contrast, bid–ask spreads on NASDAQ, the London Stock Exchange, and the CBOE are found to narrow near the close by Chan, Christie, and Schultz (1995a), Kleidon and Werner (1993), and Chan et al. (1995b), respectively.

Inventory Models

Bid–ask spreads reward market makers for bearing the risk of holding inventory. Amihud and Mendelson (1980) developed a model for specialists whereby spreads are widened as inventory imbalances accumulate. Lee et al. (1993) found evidence linking spreads to inventory control costs; in particular, higher trading volume is associated with wide spreads. Hence, for a specialist structure, a U-shaped intraday pattern of spreads is predicted because a single market maker may be forced to accumulate unwanted inventories during peak trading volumes, whereas competing market makers will be (individually) less likely to accumulate such positions. Further, Chan et al. (1995b) suggest that specialists and market makers may differ in their ability to manage imbalances by using their bid and ask quotes. Market specialists cannot execute orders on only one side of a spread, whereas competing market makers can set quotes to attract trades on only one side of the spread (and thus enhance their ability to avoid unwanted inventories).

Information Models: The Adverse Selection Problem

Glosten and Milgrom (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990) focused on the impact of information asymmetries on bid–ask spreads. In their models, the following agents are active in the market: market makers, informed traders, and liquidity traders. Some make a distinction between liquidity traders (who are forced to trade at a given time of day regardless of cost) and discretionary liquidity traders. The market maker is at an informational disadvantage relative to informed traders, and this is termed the adverse selection problem. Spreads must therefore be wide enough to ensure that the gains from trading with the uninformed agents exceed the losses associated with trading with the informed agents. Admati and Pfleiderer (1988) predicted narrow spreads when volume is high and prices are more volatile, while Foster and Viswanathan (1990) predicted narrow spreads when volume is high and prices are less volatile.

Discriminating between Competing Explanations

The distinction between specialist and multiple market maker institutional structures has provided one possible way of improving the ability to discriminate between competing theories of the bid–ask spread. Chan et al. (1995b) compared the intraday behavior of spreads for a sample of NYSE stocks and their associated options traded on the CBOE. The former is a specialist market, while the latter involves multiple market makers. Further, information (whether public or private) affecting a stock will also influence the associated call and put options. Consequently, they attempted to distinguish among the influence of market structure, adverse selection, and inventory control for the intraday patterns. They concluded that higher uncertainty at the opening of both markets can explain the wide spreads observed, but that information cannot then explain wide stock spreads and narrow option spreads at the close. The narrow option spreads are therefore likely to arise from a differing market structure.

DATA AND ESTIMATION METHODOLOGY

Data

Stock index options are traded by open outcry at LIFFE in a competing market maker environment from 08:35–16:10 Greenwich Mean Time (GMT), with price reporters present to record quotes and trades. The market is order driven with quotes generated on request. The recorded quotes reflect the best bid and ask prices offered by the crowd and the limit board at the time. The data sample consists of all quotes for American-style Financial Times-Stock Exchange (FT-SE) 100 index options at LIFFE from 4 January 1993 to 31 March 1994. The data base contains the time of the quote, expiry month, exercise price, call or put, matched bid and ask quotes, and the current level of the underlying asset. Prices are quoted in index points and the minimum price movement is 0.5 index points, which has a value of £5.

Only nearest-the-money front-month call options are examined here. Contracts with less than ten days to maturity are omitted because the volume is declining and prices become erratic as market makers refuse to take on inventory. The contracts examined are the most liquid and hence offer frequent observations, and their use avoids any bias due to large or small spreads on long maturity contracts or those away from the money. All qualifying bid–ask spreads are used in the probit analysis, resulting in a sample of 19,181 observations.[1]

[1]It is likely that with higher options prices, price makers will widen the absolute spread to maintain the proportional spread at a similar level. The sampling controls for this by only examining at-the-money and near-maturity contracts because their prices will be constrained within a relatively narrow range.

TABLE I

Values Taken by the Bid–Ask Spread on American-Style At-The-Money, Front-Month Call Options on the FT-SE 100 Index

Index Points	*Number of Observations*	*Percentage of Sample*
1	2,442	12.7
2	3,840	20.0
3	4,612	24.0
4	4,161	21.7
5	3,696	19.3
Total	18,751	97.8

Notes: Sample of 19,181 observations.

Table I shows the frequency distribution of the bid–ask spread: Spreads of 1, 2, 3, 4, and 5 index points account for 97.8% of observations.[2] Similarly, Bollerslev and Melvin (1994) find that four integer values of the spread account for 97% of quotes in their foreign exchange data set. The modal value of the bid–ask spread is 3 index points. With closing values of the FT-SE 100 index ranging from 2737.6 to 3520.3 during the sample period, the modal spread is about 0.1% of the index value. The average quoted spread for a constituent of the FT-SE 100 index at this time is about 0.7% of the index level (see London Stock Exchange Quarterly, winter 1993 through spring 1995). A near-the-money option with a delta of 0.5 would then be expected to have a minimum spread of 0.35% (0.5 $\times$ spread on asset). However, market makers in index options generally base prices on the index futures price rather than the spot price of the index. As the spread on the FT-SE 100 index futures is around 0.1%, this would give a minimum expected spread of 0.05% (0.5 $\times$ 0.1), which is consistent with the results.

Explanatory Variables

This article studies interactions among the bid–ask spread and volatility, trading activity, and market closure. The primary variable of interest is volatility, because periods of higher volatility are associated with infor-

[2]Given the minimum tick size of 0.5 index points, these represent 2, 4, 6, 8, and 10 tick spreads. This also highlights a pattern of price clustering in this market whereby prices which are not multiples of full index points are extremely rare in both quotes and trades. For all FT-SE 100 index options during the sample period, 98% of bids and asks and 96% of trades occur at multiples of full index points. In other words, the market generally operates as if the minimum tick were 1 index point not 0.5 index points. Those observations which are not at multiples of full index points tend to be in relatively low price options contracts such as those which are out-of-the-money or of short maturity.

mation arrival and uncertainty. At such times, market makers are expected to widen spreads for both asymmetric information and inventory reasons, which implies a positive relationship between the spread and option market volatility. However, of the determinants of options prices, the volatility of the underlying asset is clearly the most important. If underlying volatility increases, options prices will rise due to the increased probability of exercise. Also, market makers in options will face a higher level of risk because changes in the index level could mean that the options held lose value or even become worthless, and thus operate wider spreads.

Each observation of the bid–ask spread is matched with observations of three volatility estimates, a measure of trading activity during the interval when the spread is observed, and opening (closing) dummy variables given the value, 1, if the spread is observed in the first (last) five minutes of the day and 0 otherwise. Since volume data are not directly available, a proxy is obtained by dividing the trading day into 91 five-minute intervals, and calculating the number of quotes during each interval which has a spread observation.[3] Figure 1 plots the distribution of the volume of quotes and trades across the trading day, and shows a clear U-shaped plot in both.[4] It would be desirable to include the level of competition among market makers as an explanatory variable, but unfortunately this cannot be obtained for this market. However, discussion with LIFFE staff reveals that it is expected to be reasonably stable over the sample period.

The use of dummy variables at the open and close of trading is motivated by the contrast between a U-shaped pattern reported for several specialist markets [e.g., McInish and Wood (1992) for the NYSE] and a narrowing of spreads near the close reported for markets with competing market makers [e.g., Chan et al. (1995b) for the CBOE]. Figure 2 presents the intraday pattern in mean absolute and percentage spreads across all days for near-the-money, near-maturity calls. Spreads are wide at the market open and then quickly decrease to the level around which they fluctuate for the rest of the day. However, there is also a narrowing of spreads toward the end of the day.

The three measures of volatility used are EGARCH models of option ask returns and underlying index returns, and implied volatility.[5] Nelson's

[3]The number of trades per five-minute interval is also used as an alternative proxy, and produces very similar results.

[4]Theory suggests that the pattern can be explained by the presence of information traders early in the day acting on information accumulated overnight, and the presence of liquidity traders at the end of the day who wish to adjust positions in anticipation of the nontrading period overnight.

[5]The Akaike information criteria and residual diagnostics are used for selecting the order of the model. Other volatility models are also tested including generalized autoregressive conditional het-

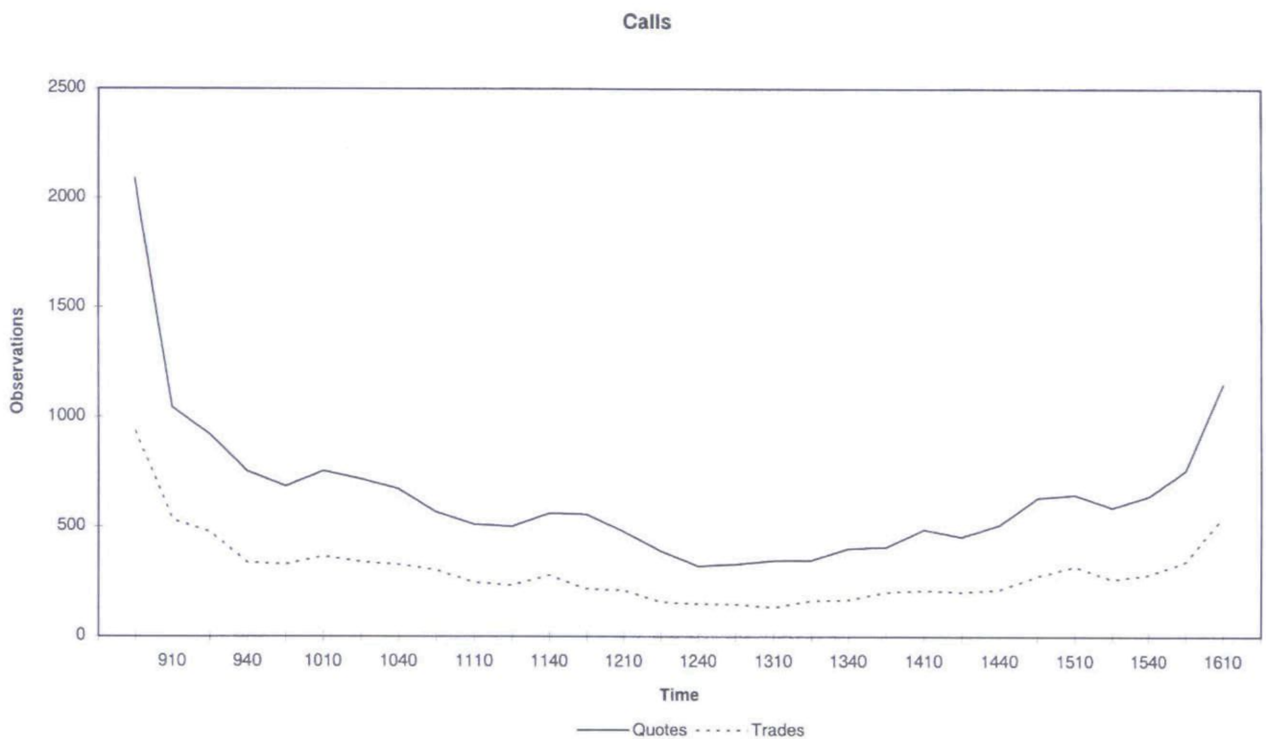

FIGURE 1
Total quote and trade frequency at 15-minute intervals.

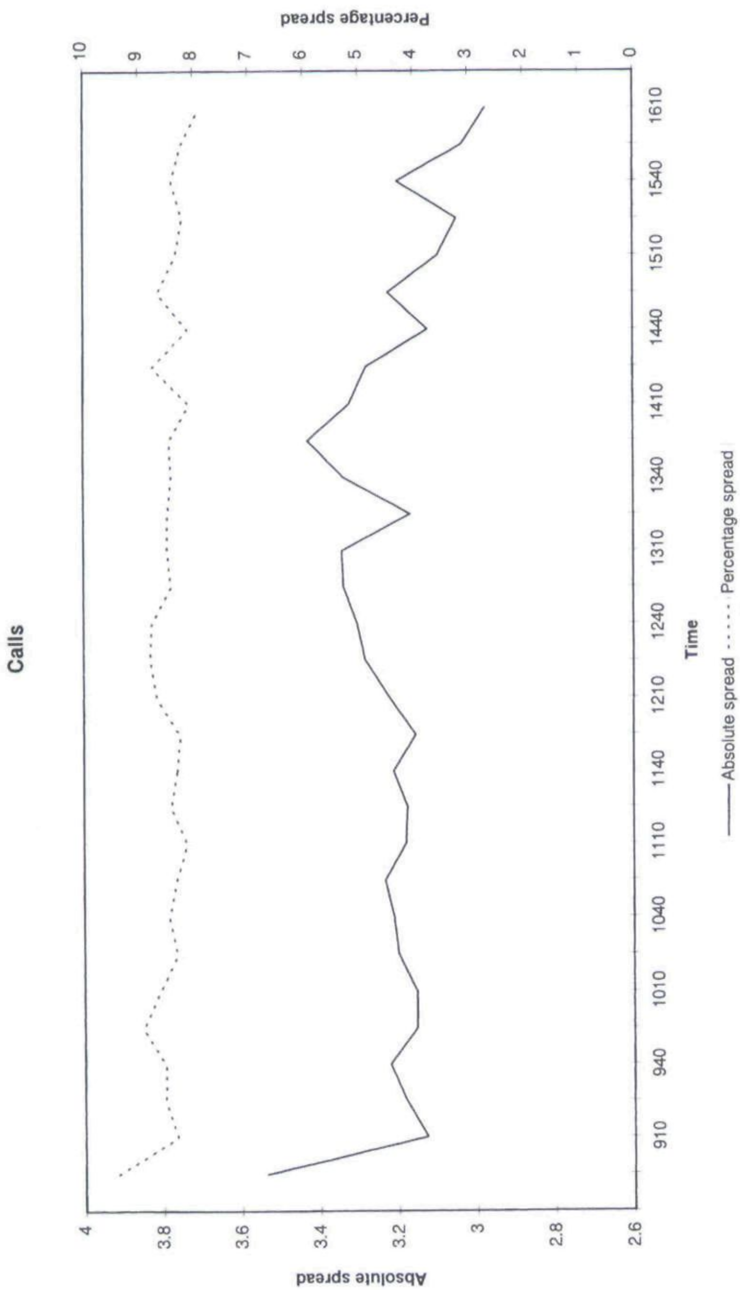

FIGURE 2
Mean absolute and mean percentage spreads at 15-minute intervals.

TABLE II

EGARCH(1,1) Model as a Measure of Options Market Volatility and Underlying Stock Index Volatility

	Option Returns	*Underlying Index Returns*
a_0	−0.0009 (−0.73)	3.8×10^6 (1.12)
a_1	−0.2801 (−21.90)	0.0707 (13.09)
b_0	−0.2590 (−5.06)	−0.1224 (−25.50)
b_1	0.9251 (79.00)	0.9909 (3303.0)
b_2	0.2870 (16.48)	0.0222 (24.67)
b_3	0.1143 (2.45)	1.4128 (19.60)

Notes: In the exponential GARCH model developed by Nelson (1990), the variance, h_i, is an asymmetric function of past innovations as follows:

$$r_i = a_0 + a_1 r_{i-1} + \varepsilon_i$$
$$\varepsilon_i \sim N(0, h_i)$$
$$\ln h_i = b_0 + b_1 \ln(h_{i-1}) + b_2\, g_{i-1}$$

where r_i is the return based on two consecutive ask prices in the case of options market volatility and two consecutive values of the FT-SE 100 index (matched with the spread observations) in the case of underlying market volatility, i refers to the sequence of quotes, and

$$g_i = |z_i| - \surd(2/\pi) - b_3 z_i$$
$$z_i = \varepsilon_i/\surd h_i$$

(1990) EGARCH specification models the variance, h_i, as an asymmetric function of past innovations. The following EGARCH(1,1) model is used as a measure of both options market and underlying volatility:

$$r_i = a_0 + a_\mathrm{i}\, r_{i-1} + \varepsilon_i$$

$$\varepsilon_i \sim \mathrm{N}\,(0, h_i)$$

$$\ln h_i = b_0 + b_1 \ln(h_{i-1}) + b_2\, g_{i-1} \tag{1}$$

where r_i is the return based on two consecutive ask prices in the case of options market volatility and two consecutive values of the FT-SE 100 index (matched with the spread observations) in the case of underlying market volatility, i refers to the sequence of quotes, and

$$g_i = |z_i| - \surd(2/\pi) - h_3\, z_i$$
$$z_i = \varepsilon_i/\surd h_i$$

The estimated parameters are presented in Table II.

eroskedasticity (GARCH) (see Bollerslev, 1986) and GJR-GARCH (see Glosten, Jagannathan, and Runkle, 1993), but the results are qualitatively unaffected. The use of option ask prices is consistent with Bollerslev and Melvin (1994), but estimations using midpoint prices produce similar results.

The implied volatility estimates are derived using the Black (1976) model, which is a modification of the original Black-Scholes formula, and is specified as follows:

$$C = e^{-rT}\, S\, N(x_1) - e^{-rT}\, X\, N(x_2) \tag{2}$$

where

$$x_1 = [\ln(S/X) + (0.5\,\sigma^2)T]/\sigma\sqrt{T} \tag{3}$$

$$x_2 = x_1 - \sigma\sqrt{T} \tag{4}$$

C is the midpoint call option price, r is the risk-free interest rate (proxied by the London interbank three-month rate), T is the time to expiry in years, S is the level of the underlying index, $N(x)$ is the normal distribution function, X is the exercise price, and σ is the volatility (the standard deviation of returns over the remaining life of the option).[6] With the exception of σ, all the parameters of eq. (2) can be observed or estimated reliably. To solve for implied volatility, Brenner and Subramanyam (1988) suggest the initial approximation:

$$\sigma \approx (C/S)\,(1/(0.398\sqrt{t})) \tag{5}$$

Each bid–ask spread is thus matched with a value of implied variance.

Ordered Probit

The selection of ordered probit as the estimation method is driven by its usefulness in capturing the relations between discrete valued dependent variables and continuous valued regressors. The spread data are clearly not continuously distributed, and Bollerslev and Melvin (1994) note that "such lack of continuity suggests that pursuing stochastic processes with continuous state spaces will not represent the spread data very well." In a related context, Hausman, Lo, and McKinlay (1992) note that "ordered

[6]Because it does not account for the early-exercise possibility of American-style options, the Black model overestimates implied volatility. Jorion (1995) uses the Black model to price American-style options and reports that with typical parameter values, the model overestimates a 12% true volatility by reporting a value of 12.02%. Recently proposed stochastic volatility models should price options more accurately, but Jorion (1995) notes that no published research has recovered the implied standard deviation from a stochastic volatility model, due to computational costs and problems in estimating the required additional parameters of the volatility process. Also, pricing differences between Black-Scholes and other models are minimized for at-the-money, front-month contracts as used here. Further, previous research (e.g., Stein, 1989) shows that implied volatility from at-the-money options is the most accurate implied volatility proxy for future realized volatility.

probit is perhaps the only specification that can easily capture the impact of explanatory variables . . . while also accounting for price discreteness." Hausman et al. (1992) also demonstrate the advantages of ordered probit over simple regression in this context, while Long (1997) cites other examples of the risk of misleading results from using simple regression with limited dependent variables.

The ordered probit model was developed by Aitchison and Silvey (1957), Ashford (1959), and Gurland, Lee, and Dahm (1960). For a detailed discussion see Greene (1991), Long (1997), or Maddala (1983). For applications in a related context, see Hausman et al. (1992) and Bollerslev and Melvin (1994). In this study, the observed bid–ask spread, S_i, is assumed to take on only a fixed number of discrete values, $a_1, a_2, \ldots a_n$, with the continuous random variable, S_i^*, defined by

$$S_i^* = \delta_0 + \delta' X_i + \varepsilon_{S,i} \tag{6}$$

where the vector, X_i, denotes a set of predetermined variables that affect the conditional mean of S_i^*, and $\varepsilon_{S,i}$ is conditionally normally distributed with mean zero and variance, $\sigma^2_{S,i}$. The i subscript refers to the sequence of quotes and not calendar time. To allow for conditional heteroskedasticity in the spread, the logarithm, $\sigma^2_{S,i}$, is parameterized as a linear function of W_i, which is also a set of predetermined explanatory variables.

$$\delta^2_{S,i} = [\exp(\gamma' W_i)]^2 \tag{7}$$

The model relates the observed spreads to S_i^* via

$$S_i = a_j, \text{ iff } S_i^* \in A_j, j = 1, 2, \ldots n \tag{8}$$

where the A_j's form an ordered partition of the real line into n intervals. The probability that the spread takes on the value, a_j, is equal to the probability that S_i^* falls into the appropriate partition, A_j. Although the spread can be any number of ticks, the evidence in Table I motivates a restriction to five groups and, therefore, four partition parameters. The group, a_1, is for spreads $(S_i) \leq 1$ index point (2 ticks); a_2 is for $1 < S_i \leq 2$; a_3 is for $2 < S_i \leq 3$; a_4 is for $3 < S_i \leq 4$; and a_5 is for $S_i > 4$. The methodology allows each state to represent multiple values of the spread: e.g., the first category represents spreads of 1 or 2 ticks. The corresponding intervals for the unobservable latent variable, S_i^*, are defined by

$$A_1 \equiv (-\infty, \mu_0]$$

$$A_2 \equiv (\mu_0, \mu_1]$$

$$A_3 \equiv (\mu_1, \mu_2]$$

$$A_4 \equiv (\mu_2, \mu_3]$$

$$A_5 \equiv (\mu_3, \infty) \tag{9}$$

Ordered probit allows the data to determine the partition parameters, μ_i, the coefficients, δ, of the conditional mean, and the coefficients, γ, of the conditional variance, $\sigma^2_{S,i}$. Following standard practice, the value for μ_0 is normalized to zero (see Bollerslev and Melvin, 1994).

The model used here is estimated by maximum likelihood and is specified as follows:

$$S_i^* = \delta_0 + \delta_1\,\delta_i^2 + \delta_2\,V_i + \delta_3\,D1_i + \delta_4\,D2_i + \varepsilon_{S,i}$$

$$\sigma^2_{S,i} = [\exp(\gamma_1\,\sigma_i^2 + \gamma_2\,V_i)]^2 \tag{10}$$

where σ_i^2 is the volatility measure (EGARCH estimate of options market volatility and both EGARCH and implied estimates of the volatility of the underlying index), V_i is the number of quotes in the five-minute interval in which the spread is observed (a proxy for trading activity), $D1_i$ is an indicator variable taking the value 1 if the spread is observed in the first five-minute interval of the day and 0 otherwise, and $D2_i$ takes the value, 1, if the spread is observed in the last five-minute interval of the day and 0 otherwise.

RESULTS

Maximum likelihood estimates for the ordered probit model in eq. (10) are presented in Table III.[7] There appears to be a lack of theoretical and empirical literature comparing option market volatility and underlying market volatility as determinants of bid–ask spreads. The first model in the table uses EGARCH estimates of options market volatility. The coefficient on options market volatility is insignificant (and indeed negative), implying the counterintuitive observation that there is no direct

[7]The estimation is conducted using PC-TSP on a Pentium 75 MHz and the run time is approximately 20–30 minutes for each probit model.

TABLE III

Coefficients for the Ordered Probit Model in Eq. (10)

	Estimate (t-Statistic)		
Parameter	*EGARCH (1,1) Model of Options Price Volatility*	*Implied Volatility*	*EGARCH (1,1) Model of Underlying Index Volatility*
δ_0	1.679 (54.7)[b]	1.164 (29.7)[b]	1.035 (24.3)[b]
δ_1	−0.416 (−1.1)	25.044 (25.6)[b]	1.9×10^6 (25.8)[b]
δ_2	−0.127 (−22.5)[b]	−0.160 (−21.1)[b]	−0.161 (−21.1)[b]
δ_3	0.865 (16.3)[b]	1.160 (16.2)[b]	1.127 (16.0)[b]
δ_4	−0.147 (−2.7)[b]	−0.166 (−2.3)[a]	−0.176 (−2.5)[a]
γ_1	−0.001 (−0.0)	5.776 (16.3)[b]	3.7×10^5 (11.3)[b]
γ_2	0.041 (10.7)[b]	0.050 (13.0)[b]	0.047 (12.3)[b]
μ_1	0.906 (101.0)[b]	1.041 (85.8)[b]	1.024 (77.2)[b]
μ_2	0.849 (112.5)[b]	0.990 (89.3)[b]	0.971 (79.5)[b]
μ_3	0.846 (112.2)[b]	1.004 (84.7)[b]	0.985 (75.4)[b]
LR	995.8[b]	2486.4[b]	2462.2[b]

Notes: δ_0 is the constant; δ_1 is the coefficient on volatility, δ_2 is the coefficient on trading activity, δ_3 is the coefficient for the opening five-minute period, δ_4 is the coefficient for the closing five-minute period, μ_1, μ_2, and μ_3 are the partition parameters, and γ_1 and γ_2 are the parameters of eq. (10) allowing for conditional heteroskedasticity in the spread. LR denotes the likelihood ratio statistic for the joint significance of all explanatory variables, i.e., tests the null hypothesis that $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \gamma_1 = \gamma_2 = 0$. Reported *t*-statistics are based on standard errors computed from analytic second derivatives (Newton method). Standard errors are computed also from covariance of analytic first derivatives (Berndt-Hall-Hall-Hausman method) and from analytic first and second derivatives (Eicker-White method), but the inferences are unchanged.
[a]Significance at the 1% level.
[b]Significance at the 5% level.

relationship between the spread and options market volatility. The coefficient on γ_1 is very close to zero and indicates that options market volatility does not impact on heteroskedasticity of the spread either.

Contrasting results are reported in the second and third models in Table III for the impact of underlying stock index volatility on bid–ask spreads, with both implied volatility and EGARCH estimates producing similar results. The δ_1 coefficients indicate that there is a positive and significant (at the 1% level) effect of underlying volatility on the spread. The primary difference between the two sets of results is in the scale of the volatility coefficients. The much higher values for the EGARCH volatility coefficients are a result of the model being a measure of the one-step ahead volatility, whereas implied volatility is a measure of the volatility over the remaining life of the options contract. The overestimation of implied volatility by the Black (1976) model is far too small to account for the difference (see footnote 6). Further, the coefficients on γ_1 indicate the importance of underlying stock index volatility on heteroskedasticity of the spread, with both having a positive and significant impact on $\sigma^2_{S,i}$.

For all parameters except those on volatility, all three cases produce similar results and the significance levels for all other variables are quite robust across volatility estimates. A significant (at the 1% level) and negative coefficient is observed for the trading activity variable in each case, which is consistent with the hypothesis that a more active market results in narrower bid–ask spreads. This is consistent with the predictions of Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) which suggest that narrow spreads and high volume will coincide, but contrasts with the evidence of Lee et al. (1993) for a specialist system of market making.

A significant (at the 1% level) and positive coefficient is observed on the market open dummy in each case, which confirms the hypothesis of wider spreads at the start of the trading day. The market close dummy has a consistently significantly negative coefficient. The relative size of the coefficients on the open and close dummies suggests that the reduction in spreads toward the end of the day is not as marked as the wider spreads at the open. The absolute size of the open dummy is approximately six times larger than the close dummy, which is comparable with the results of Chan et al. (1995b) for the CBOE. The theoretical literature offers no predictions for this relative magnitude.

Further, the coefficients on γ_2 indicate the importance of trading activity on the heteroskedasticity of the spread, with a positive and significant impact on $\sigma^2_{S,i}$ in all three cases. The partition boundaries (μ_1, μ_2, and μ_3) are estimated with a high degree of precision in each case, as indicated by the very large t-statistics, which highlights the validity of the use of ordered probit to model the bid–ask spread. These are cumulative estimates, e.g., the second partition (μ_2) for the EGARCH options market volatility case in Table III is at 1.755 (0.906 + 0.849).

The likelihood ratio statistic tests the joint significance of the explanatory variables, i.e., tests the hypothesis that $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \gamma_1 = \gamma_2 = 0$. The null is clearly rejected in each case according to the χ^2_6 distribution. It is important to note that the ratio is similar for the two cases using underlying stock market volatility, but is substantially reduced in the estimation employing options market volatility. This reflects the small and insignificant coefficients on δ_1 and γ_1 in that model.

Table IV reports further results from more direct tests of the relative impact of each volatility measure on the bid–ask spread. The same methodology and data as in Table III are employed, but more than one volatility measure is included in each estimation. The first model represents the case where all three volatility measures are included in the spread mean and variance equations. The results support the evidence of Table III in

TABLE IV

Coefficients for Ordered Probit Models Including Both Options Price Volatility and Underlying Stock Index Volatility as Independent Variables

	Estimate (*t*-Statistic)		
Parameter	OPV (δ_1 and γ_1), IV (δ_2 and γ_2), and UIV (δ_3 and γ_3)	OPV (δ_1 and γ_1) and IV (δ_2 and γ_2)	OPV (δ_1 and γ_1) and UIV (δ_3 and γ_3)
δ_0	0.757 (15.3)[b]	1.154 (28.9)[b]	1.033 (23.8)[b]
δ_1	0.676 (1.3)	0.456 (0.9)	0.249 (0.5)
δ_2	20.210 (18.3)[b]	25.087 (25.4)[b]	n.a.
δ_3	1.6×10^6 (19.2)[b]	n.a.	1.9×10^6 (25.6)[b]
δ_4	−0.184 (−20.3)[b]	−0.160 (−21.0)[b]	−0.161 (−21.0)[b]
δ_5	1.338 (16.0)[b]	1.156 (16.1)[b]	1.129 (15.9)[b]
δ_6	−0.190 (−2.3)[a]	−0.165 (−2.3)[a]	−0.176 (−2.5)[a]
γ_1	0.036 (0.1)	−0.039 (−0.1)	0.150 (0.5)
γ_2	4.241 (10.9)[b]	5.768 (16.3)[b]	n.a.
γ_3	3.3×10^5 (9.0)[b]	n.a.	3.7×10^5 (11.3)[b]
γ_4	0.050 (13.1)[b]	0.050 (13.0)[b]	0.047 (12.3)[b]
μ_1	1.110 (73.1)[b]	1.040 (84.1)[b]	1.026 (76.0)[b]
μ_2	1.062 (74.1)[b]	0.989 (87.4)[b]	0.973 (78.2)[b]
μ_3	1.088 (69.6)[b]	1.004 (83.1)[b]	0.986 (74.3)[b]
LR	3101.0[b]	2485.6[b]	2462.6[b]

Notes: The variables are defined as in Table III. OPV is the EGARCH(1,1) model of options price volatility, IV is implied volatility, and UIV is the EGARCH(1,1) model of underlying index volatility. δ_0 is the constant, δ_4 is the coefficient on trading activity, δ_5 is the coefficient for the opening five-minute period, δ_6 is the coefficient for the closing five-minute period, μ_1, μ_2, and μ_3 are the partition parameters, and γ_i allows for conditional heteroskedaticity in the spread with γ_4 denoting the coefficient on trading activity. LR denotes the likelihood ratio statistic for the joint significance of all explanatory variables. Reported *t*-statistics are based on standard errors computed from analytic second derivatives (Newton method). n.a., not applicable.

[a]Significance at the 1% level.

[b]Significance at the 5% level.

that options market volatility is insignificant while measures of instantaneous and expected underlying volatility have significant coefficients. For options market volatility, the δ_1 coefficient is now positive but still small and insignificant, while the γ_1 coefficient is also insignificant. The other parameters of the model (trading activity, market closure dummy variables, and partition parameters) are very similar in significance to Table III. The likelihood ratio for this model is the highest of all specifications examined.

The second and third models in Table IV present estimation results where options market volatility is tested directly against implied volatility and the EGARCH model of underlying volatility in turn. Again, options market volatility coefficients are all insignificant. In both cases, the other parameters are practically unchanged compared to the corresponding cases which exclude options market volatility in the second and third models of Table III. Also, the likelihood ratios are basically unimproved by inclusion of options market volatility. In sum, these results are clear evidence that the bid–ask spread on FT-SE 100 stock index options is driven by underlying market volatility rather than options market volatility.

CONCLUSIONS

This article uses ordered probit to investigate the impact of price risk, trading activity, and market closure on bid–ask spreads in the U.K. index options market. The bid–ask spread is found to be driven by underlying volatility but not by volatility in the options market itself, a finding which is robust across various model specifications. This contrasts with previous work in this area examining assets other than options which found direct relationships with own market volatility (e.g., Bollerslev and Melvin, 1994). The existence of a relationship with underlying volatility rather than options market volatility is caused by the importance of underlying volatility in pricing options. Higher underlying volatility causes increases in options prices because the probability of exercise is greater. Also, the options market makers will face a higher level of risk because the options held may lose value or even become worthless (move out-of-the-money) as a result of adverse movements in the underlying index. Dealers, therefore, require a premium on the spread.

The spread is inversely related to trading activity, which is consistent with the predictions of Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) that narrow spreads and high volume will coincide, but contrasts with the evidence of Lee et al. (1993) for a specialist market (the NYSE). The Foster and Viswanathan (1990) model is supported in the observation of narrow spreads when volume is high and prices are less volatile, in contrast to the Admati and Pfleiderer (1988) prediction of narrow spreads when volume is high and prices are more volatile.

Spreads are found to be relatively wide at the open and relatively narrow near the close. This is consistent with Chan et al. (1995a, 1995b) and supports the hypothesis that market structure affects spreads behavior. Wide spreads at the market open are explained by the theories relating to information asymmetry and uncertainty. The end of the day is a time of inelastic demand, and for market makers with monopolistic power this offers potential for increased rewards through wider spreads (e.g., Brock and Kleidon, 1992). In an environment of competing market makers, such potential does not exist and wider spreads would not be expected. However, a narrowing of spreads suggests other factors. Chan et al.

(1995a) hypothesized that this is explained by the price makers' desire to avoid holding inventory (open positions) overnight. To achieve this, they narrow the spread to attract the required trades. Though theory offers no indication of the expected relative magnitude of the open and close effects, the coefficient on the dummy variable at the market open is several times larger than that at the market close [which is consistent with Chan et al. (1995b)].

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