The Informativeness of Trades and Quotes in the FTSE 100 Index Futures Market

BART FRIJNS* and YIUMAN TSE

This study examines the informativeness of trades and quotes in the FTSE 100 index futures market. Using a tick time model, we decompose the innovation in the efficient price into a trade-induced and a quote-induced part. For the extensive time period from 2001 to 2011, we find that trades are highly informative, explaining about 80% of the innovation in the efficient price. Large trades are more informative than smaller trades. We observe a noticeable upward trend in the contribution of trades, but also notice large drops in price informativeness around the recent global financial crisis and the European debt crisis. These drops could be attributed to noise trading during volatile periods. © 2014 Wiley Periodicals, Inc. Jrl Fut Mark 35:105–126, 2015

1. INTRODUCTION

The question of whether trading in index futures contracts is informative or mainly driven by noise has received considerable attention. There are two opposing views on this issue. Stein (1987), for example, argues that futures trading by poorly informed speculators can destabilize the stock market. Index futures may attract more noise traders as they provide considerable leverage. In contrast, Danthine (1978), among others, shows that futures markets improve market depth and reduce volatility because the cost to informed traders of responding to mispricing is reduced. Futures may contain more information than the underlying if these contracts complete markets and disclose information that is not easily revealed in the underlying. Both arguments have found empirical support.[1]

The question on the informativeness of trades is an important one because if the index futures market mainly attracts noise traders, the index futures market may have a destabilizing effect on the underlying cash market. However, if the index futures market attracts informed traders, then these markets complete the underlying cash market and add to its price discovery

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Bart Frijns is a Professor of Finance at Auckland University of Technology, Auckland, New Zealand. Yiuman Tse is Peter G. Schick Professor of Finance at University of Missouri–St. Louis, St. Louis, Missouri. We are grateful to an anonymous referee, Bob Webb (editor), Steven Li (discussant), and the participants at the International Conference on Futures and Other Derivative Markets in Beijing, China for valuable comments.

*Correspondence author, Department of Finance, Auckland University of Technology, Private Bag 92006, 1142 Auckland, New Zealand. Tel: +64-9-921-9999 ext. 5706, Fax: +64-9-921-9940, e-mail: bfrijns@aut.ac.nz

Received December 2012; Accepted December 2013

[1]Bessembinder and Seguin (1992) report that index arbitrage improves market depth. Berkman, Brailsford, and Frino (2005) document empirical support for the theoretical model of Subrahmanyam (1991) by reporting higher adverse selection costs in the stocks of the FTSE 100 index than in the futures contract. In contrast, various studies have shown that derivative markets lead the cash markets, providing greater price discovery (see, e.g., Garbade & Silber, 1983 for an early reference). This recently has also been shown to be the case for the FTSE 100 index futures contracts (see Sebastião, 2010).

The Journal of Futures Markets, Vol. 35, No. 2, 105–126 (2015)

Published online 17 February 2014 in Wiley Online Library (wileyonlinelibrary.com).
DOI: 10.1002/fut.21652

and efficiency.[2] Indeed, several studies have examined the informativeness of trades in index futures markets and in particular for the FTSE 100 index futures (see, e.g., Chng, 2004; Holmes & Tomsett, 2004). These studies suggest that trades in the FTSE 100 futures contract are informative and contribute to a large proportion of the innovation in the efficient price. These previous studies have mostly focused on either the floor-trading system (Holmes and Tomsett) or the change from floor to electronic trading (Chng).[3] In addition, both studies estimate reduced-form models.

In this study, we examine the informativeness of trades in the FTSE 100 futures contracts by empirically implementing a model similar to Frijns (2006). This model is analogous to those developed by Hasbrouck (1991a, 1991b) and Madhavan, Richardson, & Roomans (1997), but allows for the assessment of the impact of time and size on the informativeness of trades. The model is based on the notion that trades and quotes share the same common underlying trend, often referred to as the efficient price, but deviate temporarily from this efficient price due to microstructure noise. Both trades and quotes contribute to the innovations in the efficient price, and these contributions determine the informativeness of trades and quotes.[4] The nature of the model allows us to assess the impact of duration (time between trades and quotes) and size on the informativeness of trades and quotes. In addition, the model provides estimates for the implied quoted and effective spreads as in Madhavan et al. (1997).

We estimate our model over an extensive time period from January 2001 to December 2011. Given that our model uses all trades and quotes as they arrive at the market, we can estimate the model on a daily basis and investigate the variation in the relative contributions of trades and quotes over time.

We find that, on average, trades are highly informative about the innovation in the efficient price (on a daily basis, about 80% of the innovation in the efficient price is due to trades). These findings are important as they suggest that index futures markets contain valuable information and complete the underlying cash market. When examining the time variation in the contribution of trades to innovations in the efficient price, we observe that these contributions have increased over time. Yet, we notice considerable decreases in the contributions of trades during the global financial crisis and the subsequent European debt crisis. Further analysis reveals that the contribution of trades to the innovation in the efficient price is strongly and negatively related to the FTSE 100 implied volatility index (IVI). This suggests that during periods of high volatility (such as crisis periods) more noise trading happens in these contracts.

We also find that large trades are more informative than smaller trades and the variation of variance contribution of trades over time is associated with large trades. Since large trades are more informative and price informativeness deteriorates during volatile periods, the overall results support the positive relation between institutional investors (who submit large trades) and uninformed trading. In particular, when the stock market is volatile, institutional investors may use index futures more for uninformed hedging.

In addition to these findings, our model also provides estimates for the quoted and effective half-spreads and the impact of time (duration between trades and quote innovations) on the informativeness of trades and quotes. We observe that both quoted and effective spreads have decreased considerably over time. However, there is a strong positive relation

[2]Several studies have investigated the price discovery role of futures markets in relation to the underlying cash market and typically find that futures markets play a significant role (see, e.g., Booth, So, & Tse, 1999).

[3]The change from floor-based trading to electronic trading has profound impacts on the market microstructure of the futures contracts as documented by Aitken, Frino, Hill, and Jarnecic (2004), Gilbert and Rijken (2006), Ning and Tse (2009), Sebastião (2010), and ap Gwilym and Meng (2010).

[4]Note that our definition of trade informativeness is the same as Hasbrouck (1991b).

between quoted and effective spreads and market volatility. We also find that time between trades has a minor impact on the informativeness of trades. For quote innovations time is more important, where, on average, the informativeness of quotes decreases by 48.4% for quote innovations with a duration of 10 seconds relative to quote innovations within the same second.

Our work is related to several studies on the informativeness of trades. The analysis conducted in this study is closely related to Holmes and Tomsett (2004). Holmes and Tomsett decompose trades into informative and uninformative components, using the mixture of distribution hypothesis of Andersen (1996) for a sample of daily futures prices and volumes over the period January 1992 to July 1996 (floor-based trading). They find that the majority of trades are highly informative, contributing to about 90% of the innovation in the efficient price. Our work is also related to Chng (2004) who estimates an extended version of Hasbrouck's (1991a, 1991b) model for the LIFFE 100 index futures before and after the introduction of electronic trading. In line with Holmes and Tomsett, he finds that trades are highly informative in the futures index market, but reports that the informativeness of trades has decreased after the change to electronic trading, from approximately 98% in the floor-based trading environment to 80% in the electronic trading environment.

Our study extends the work of Holmes and Tomsett (2004) and Chng (2004) in several important directions. First, rather than using a reduced form model, our study uses a structural market microstructure model to assess the informativeness of trades. This allows us to directly estimate the impact of trades and quotes on the innovations in the efficient price. Second, our structural model allows us to test for the impact of time and size on the contributions of trades and quotes to the innovations in the efficient price. Third, since we estimate our model on tick-level data, we estimate the model on a day-to-day basis. This allows us to assess the time variation in the informativeness of trades and quotes. Finally, we apply our model to more recent data and the FTSE 100 index futures are traded electronically.

The remainder of this study is structured as follows. In the following section, we discuss the tick time model used in this study. In Section 3, we describe the data used in this study. In Section 4, we present the results of our tick time model and compute the daily contributions to the efficient price for trades and quotes. In this section, we also extend our model to examine the role of trade and quote size on the informativeness of trades and quotes. We conclude our study in Section 5.

2. MODEL

We develop a model to describe the price and quote dynamics for the FTSE 100 index futures. The model builds on the work of Frijns (2006) and assumes that transaction prices and quoted prices for the same asset share the same underlying common trend, also known as the efficient price.

On a given day, n, let p_i be the log transaction price of an asset of the ith transaction occurring at time t_i, where $i = 1, \ldots, I_n$. We define x_i as the trade indicator, which is equal to -1 ($+1$) if the ith trade is seller (buyer) initiated. Like Madhavan et al. (1997), we decompose the transaction price into three components, that is,

$$p_i = m_i + \phi x_i + u_i. \tag{1}$$

The first part of this decomposition is the permanent part, m_i, or the efficient price, which is a random-walk process that will be defined later. The second part captures the fact that buys and sells execute at different prices. The coefficient ϕ provides a measure for the effective cost of trade (effective half-spread). The final part is a transitory part, u_i, which contains any remaining microstructure noise.

On the same day where I_n trades are observed, we observe J_n quote innovations. Let q_j be the vector of quotes at time t_j where $j = 1, \ldots, J_n$, and t_j is the time of the jth quote innovation. Note that since trades and quotes may occur at different points in time, and because there can be more trades than quote innovations (or vice versa), I_n and J_n do not have to be the same. Similar to the decomposition in Equation (1), we can decompose the quote process, that is,

$$q_j = c + \iota m_j + v_j, \tag{2}$$

where q_j is a (2×1) vector of log quotes, c is a (2×1) vector of the form $\begin{pmatrix} -c \\ +c \end{pmatrix}$ and is a measure for the quoted half-spread, ι is a (2×1) unit vector and v_j is a (2×1) vector containing any remaining microstructure noise. m_j is the same efficient price as in Equation (1) but is measured at possibly different points in time during the day.

Because both the trade and quote processes share the same permanent component, their dynamics revolves around the efficient price process, m. We assume that this efficient price process follows a random walk, that is,

$$m_l = m_{l-1} + \sigma_l \varepsilon_l, \tag{3}$$

where σ_l captures the (time-varying) magnitude of the innovation, ε_l, in the efficient price. The efficient price process evolves in a composite time scale as information about the location of the efficient price is released whenever a transaction occurs or when a quote is innovated. Hence, new information about the location of m_l arrives to the market at time t_l, where $t_l = t_i \cup t_j$.

To determine the impact of trades and quotes on the innovation in the efficient price, we further decompose σ_l as follows,

$$\sigma_l = \tau_{TRADE,l}^{\delta^{TRADE}} \sigma^{TRADE} D_l^{TRADE} + \tau_{QUOTE,l}^{\delta^{QUOTE}} \sigma^{QUOTE} D^{QUOTE}, \tag{4}$$

where $\tau_{TRADE,l}$ is the duration between the current and previous trades, $\tau_{QUOTE,l}$ is the duration between current and previous quote innovations, σ^{TRADE} is the magnitude of the innovations in the efficient price that is due to trades, σ^{QUOTE} is the magnitude of the innovation in the efficient price due to quotes, and D_l^{TRADE} and D_l^{QUOTE} are dummy variables that are equal to one if the event occurring at t_l is a trade or a quote innovation, respectively. The parameters δ^{TRADE} and δ^{QUOTE} capture the impact of trade and quote durations, respectively, on the innovation in the efficient price.[5]

With the introduction of electronic trading, the frequency of quote innovations and trades has increased significantly and we often observe trades and quotes occurring within the

[5]Note that there are several distinctions between our model specification and that of Frijns (2006). First, Frijns includes a term that captures the joint impact of trades and quotes. This term was included as trades and quotes sometimes arrived at the same time and there was no unique ordering of the data. In our case, there is a unique ordering of the data and hence we know the exact sequence of events. We therefore do not have to include this term that captures the joint effect. Second, we capture the impact of time between trades and quotes separately in the evolution of the efficient price, whereas Frijns models the evolution of the efficient price process in a combined (trade and quote) time scale. It is worth noting that it may be difficult to compare the empirical results between Frijns and the current paper because of different data and market structures. Frijns uses individual stocks traded on Nasdaq (a dealer market) and the current paper uses FTSE index futures (a order-driven market).

same second. Therefore, we measure durations as follows,[6]

$$\tau_{k,l} = 1 + (t_{k,l} - t_{k,l-1}), \tag{5}$$

where $t_{k,l}$ and $t_{k,l-1}$ are the times of the most recent and last observation of k (trade or quote). Doing this allows us to assess the impact of trades and quotes that occur within the same second and effectively have zero duration.[7]

For the parameters of δ^{TRADE} and δ^{QUOTE} in Equation (4), the values of interest are 0.5 and 0. If the parameter value is equal to 0.5, this implies that the variance of the efficient price process is proportional to the time between events and the process is said to evolve in calendar time (e.g., the variance of a 2-minute price change is twice the variance of a 1-minute price change). If the parameter value is equal to 0, durations between events do not have an impact on the innovation in the efficient price. In this case, it is the occurrence of an event that matters, not the time between events. The process is then said to evolve in tick time (see Clark, 1973). Whenever δ's are greater than zero, it implies that when durations between events (trades, quotes) increase, these events become more informative. When δ's are less than zero, it implies that when durations between events (trades, quotes) get longer, those events become less informative. With these definitions of τ and δ, the innovations in the efficient price process, σ^{TRADE} and σ^{QUOTE}, are essentially the magnitudes of the innovations measured at zero durations.

To identify the parameters in the model described above, we rewrite the model in State Space Form. However, since we do not observe trades and quotes at the same point in time during the day, the model cannot be estimated directly. To estimate the model, we follow Frijns (2006) and Frijns and Schotman (2009). Specifically, let y_l be the observation vector that contains the most recent log prices and log quotes. Because we are only interested in the arrival of new information, we need to select those elements from y_l that are new at time t_l. Let S_l be the selection matrix that selects those elements from y_l that are updated. For example, if only a bid quote is innovated at time t_l, $S_l = (\,0 \quad 1 \quad 0\,)$ and the selection from the vector y_l works as follows

$$S_l y_l = (\,0 \quad 1 \quad 0\,)\begin{pmatrix} p_l \\ bid_l \\ ask_l \end{pmatrix} = bid_l. \tag{6}$$

Applying this selection matrix consistently throughout the model, we can write out the full model in State Space Form, that is,

$$S_l y_l = S_l \begin{pmatrix} \phi x_l \\ c \end{pmatrix} + S_l \iota m_l + S_l \begin{pmatrix} u_l \\ v_l \end{pmatrix}. \tag{7}$$

The model stated in Equation (7) can now be estimated using the Kalman Filter, where the observations that are not updated are treated as missing observations (see also Durbin & Koopmans, 2001; Harvey, 1989). We re-estimate this model for every trading day in our sample period, so that we have daily estimates of all parameters.

[6] Note that for the earlier part of our sample we only observe trades and quotes time-stamped to the nearest second, since 2005 we have data with millisecond precision. However, to be consistent over the entire sample period, we round all millisecond observations to the nearest second.

[7] In contrast to Frijns (2006) we do not normalize durations. Normalization in Frijns (2006) is required because he studies multiple assets and normalization makes the duration parameters more comparable between assets. As we only examine one asset, such normalization is not necessary.

3. DATA

We obtain tick-by-tick data for the FTSE 100 futures contracts for the period of January 2, 2001 to December 30, 2011. These data are obtained directly from LIFFE for the period of 2001 to 2004 and are obtained from the Thomson Reuters Tick History database for the period of 2005 to 2011. This dataset contains trades and quotes time-stamped to the nearest second and associated volumes. From January 2001 to June 2008, the FTSE futures contracts traded during normal LSE trading hours (8:00–16:30). In June 2008 trading hours were extended to capture trading in the US markets (8:00–21:00). Trading hours were further extended in October 2010 (1:00–21:00) to capture the Asian market. Over the entire sample period, we have a total of 2,740 trading days.

From the tick-by-tick dataset, we select the most liquid nearby contracts to estimate our model. Using the Lee and Ready (1991) approach, we classify a trade as a buy (sell) if it takes place at the ask (bid). For trades occurring within the quoted bid–ask spread, we apply the tick rule.

In Table I, we provide some summary statistics for our sample. In Panel A, we report summary statistics for the normal trading hours (08:00–16:30). We first report the average number of trades and quotes per day. The FTSE 100 index futures are very liquid with an average number of daily observations close to 40,000. In the next two rows, we report the average daily number of trades and the daily number of quote innovations. Note that we only consider quote innovations in our study, that is, when a quote changed from its previous value.

TABLE I
Sample Overview

	Mean	*Median*	*SD*
Panel A: Normal Trading Hours (08.00–16.30)—Full Sample			
Total observations	39,607	27,347	34,332
Trades	14,013	10,008	11,091
Quotes	25,594	17,500	23,623
Trade duration	2.103	1	6.412
Quote duration	1.134	0	4.425
Quoted spread	0.019%	0.017%	0.027%
Panel B: Late Trading Hours (16.30–21.00) for the period June 2, 2008–December 30, 2011			
Total observations	20,265	16,167	13,328
Trades	4,728	4,121	2,408
Quotes	15,538	12,081	11,108
Trade duration	3.197	1	39.363
Quote duration	0.657	0	71.142
Quoted spread	0.027%	0.019%	0.029%
Panel C: Early Trading Hours (01.00–7.50) for the period October 4, 2010–December 30, 2011			
Total observations	2,923	1,942	4,648
Trades	346	294	231
Quotes	2,576	1,612	4,605
Trade duration	36.908	5	105.32
Quote duration	9.395	1	43.121
Quoted spread	0.055%	0.036%	0.054%

Note. This table reports summary statistics of our sample. *Total Observations, Trades, and Quotes* measure the total number of daily observations, daily trades, and daily quote innovations, respectively. *Trade* and *Quote Durations* are the time (in seconds) between the trades and quote innovations. *Quoted Spread* is computed in percentage terms as the bid minus ask quote divided by the midpoint of the bid and ask. We report the mean, median, and standard deviation.

We find approximately 14,000 trades and 26,000 quote innovations per day. Median values are lower at 10,008 and 17,500, respectively, indicating that there are some days in our sample with very high trading and quoting activity.

In the next two rows of Panel A, we report statistics on the durations between trades and quote innovations. In line with the observations from trading and quoting activity, we observe that average durations are short between trades and quote innovations, at 2.10 and 1.13 seconds, respectively.

The last row of Panel A shows the percentage quoted spread, which is 0.019%, on average, suggesting that a round-trip trade at the quoted spreads costs about 0.019% of the value of the trade. This number is slightly lower than the average percentage spread observed by Ning and Tse (2009) of 0.022% during the electronic trading sample period of June 1999 to December 2005. See also Tse (1999). Median values are slightly below the average at 0.017%, indicating right-skewness in the percentage spread.

To provide some more insight into the distributions of these variables, we show histograms of the total number of observations, trade and quote durations and percentage spread in Figure 1. In all of the histograms we can observe right-skewness in the distributions.

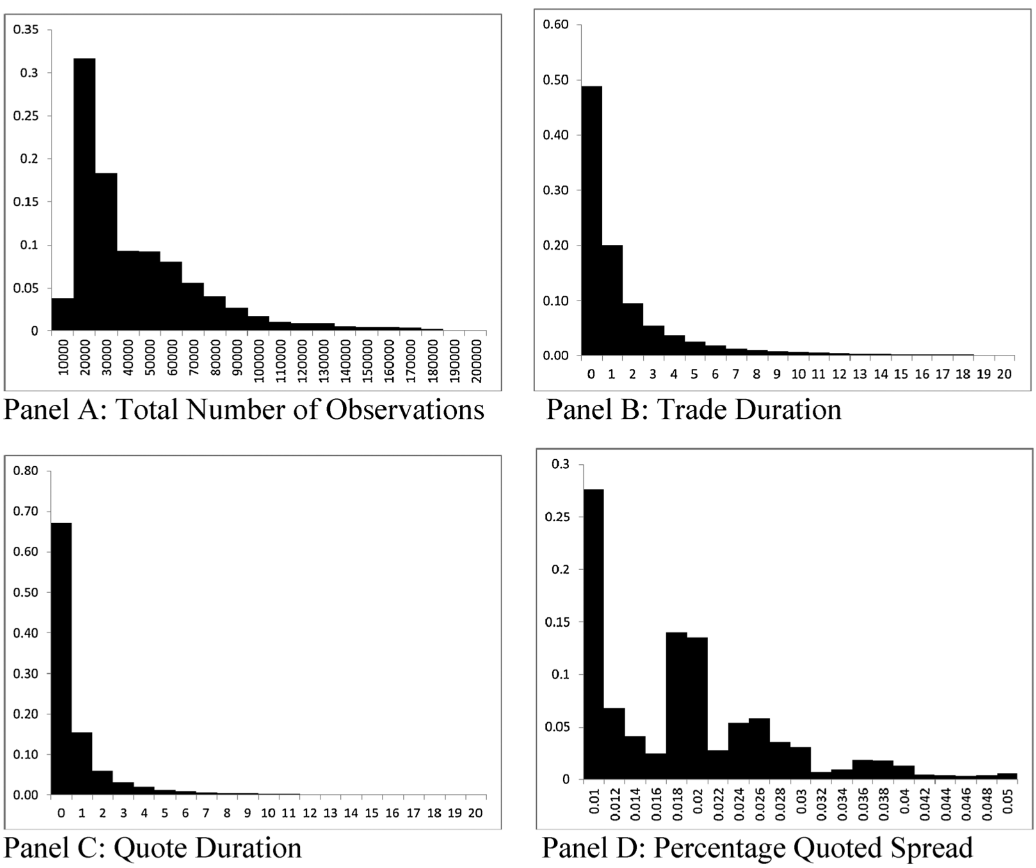

FIGURE 1
Characteristics of the sample.
Note: This figure plots various histograms that provide details on the characteristics of the sample. Panel A shows the histogram for the total number of observations per day over the period of 2001–2011. Panel B shows the histogram of the trade duration. Panel C shows the histogram of the quote duration. Panel D shows the histogram of the percentage quoted spread.

We can clearly observe the difference in the distribution of trade and quote durations. The histogram of the percentage spread reveals that its distribution is multi-modal, which is most likely a consequence of price discreteness. Note that the minimum tick size on the FTSE 100 index futures in 0.5.

In Panels B and C of Table I, we present descriptive statistics of the sessions covering the two extended trading periods. Panel B reports statistics for the extended hours after normal trading hours that were introduced in June 2008. As can be seen from the time between trades, this period has lower trading activity than the normal market session. However, quoting activity in this period seems to be higher than the normal market session. Quoted spreads in this session are also higher than during the normal trading hours. Panel C reports statistics for the extended hours before normal trading hours that were introduced in October 4, 2010. It can be seen that this period is very different from the normal market hours, with very low trading and quoting activity, and relatively high quoted spreads compared with the normal market session. Given that these extended sessions have different characteristics from the normal session, and for consistency in our estimation (as the extended sessions were only introduced later in our the sample period), we sample the data over the normal trading hours, where we remove the first and last 5 minutes of the trading day to avoid capturing any effects from the open and close of the market.

In Figure 2, we show the FTSE 100 index level and its implied volatility index (IVI). As can be seen from the index level (upper part of the graph) our sample includes the bursting of the dot-com bubble in the early part of the sample, a bull period that lasted from late 2003 to late 2007, and the recent global financial crisis and European debt crisis in the latter part of the sample. The lower part of the graph shows the evolution of the IVI. We can clearly see that the IVI peaks during the 2008 global financial crisis.

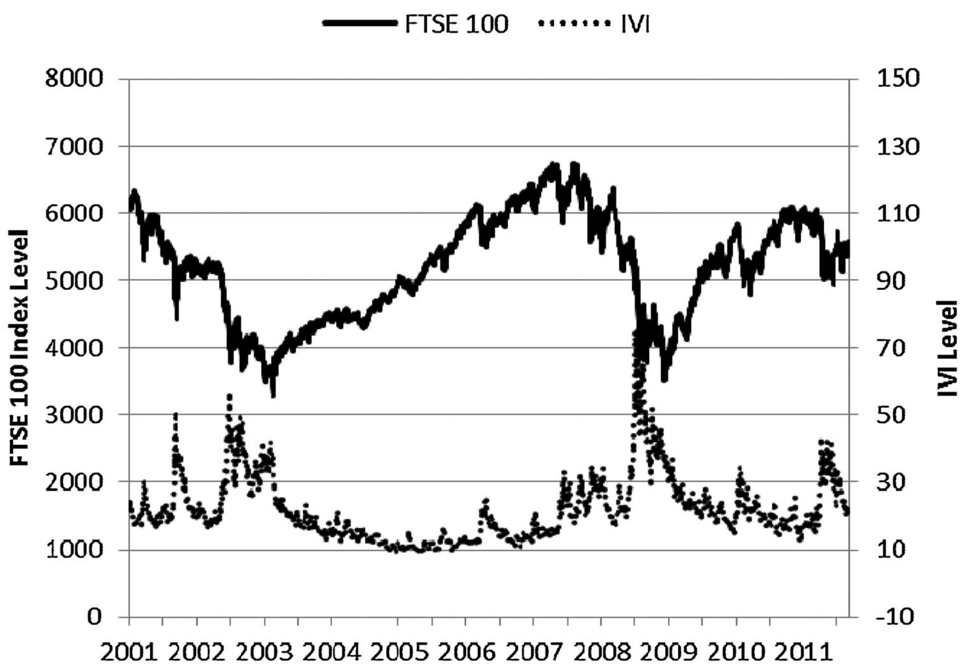

FIGURE 2

FTSE 100 index and the implied volatility index (IVI).

Note: This figure shows the FTSE 100 index level and its implied volatility index (IVI) over the period of 2001–2011. The left y-axis shows the stock index level, and the right y-axis shows the IVI level.

In Figure 3, we provide a time series plot of the log daily number of trades over the sample period. Overall, we observe that there is a positive trend in the trading activity in the FTSE 1,000 index futures. However, we note that trading activity decreases from early 2003 to the start of 2005, and hits the height during the global financial crisis period.

4. RESULTS

We present the results for the model described above. First, we discuss the tick time results, that is, the results for parameters per trade or per quote. Second, we report the results for daily variance ratios, where we aggregate the impact of trades and quotes on a daily basis. These variance ratios are similar to the informativeness measures of Hasbrouck (1991a, 1991b) and Chng (2004). Finally, we report the results for an extended version of our model, where we allow trades and quotes to have different impact on the innovation in the efficient price.

4.1. Tick Time Results

4.1.1. Quoted Versus Effective Half-Spread

In Table II, we report summary statistics on our model estimates for the quoted half-spread, c, and the effective half-spread, ϕ. Since the model is estimated in log prices, these numbers can be interpreted as percentage spreads. The last column reports ϕ/c, the ratio of effective over quoted spread.

The implied average percentage quoted half-spread is about 0.0083% (resulting in a quoted spread of 0.0166%) over the entire sample period. This is close to the observed average

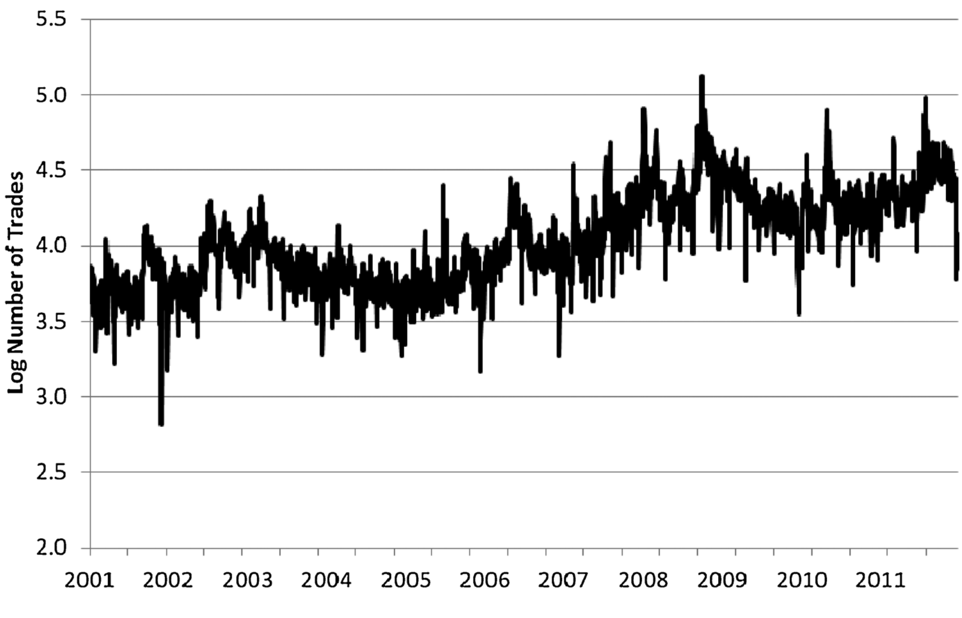

FIGURE 3
Trading activity (log number of trades) during normal market hours.
Note: This figure shows the log number of trades during normal trading hours over the period of 2001–2011.

TABLE II
Summary Statistics for the Quoted and Effective Half-Spread

	c	ϕ	ϕ/c
Mean	0.0083%	0.0053%	65.76%
T-Stat	(48.04)	(59.05)	(183.00)
SD	0.0031%	0.0016%	6.97%
5th Perc.	0.0055%	0.0036%	53.91%
25th Perc.	0.0061%	0.0042%	60.87%
50th Perc.	0.0070%	0.0048%	66.31%
75th Perc.	0.0099%	0.0063%	70.59%
95th Perc.	0.0147%	0.0084%	76.37%

Note. This table presents summary statistics for the quoted and effective half-spread as estimated by the model. *T*-statistics are computed for the daily estimates and are robust for heteroskedasticity and autocorrelations (Newey & West, 1987). We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

quoted spread of 0.019% as reported in Table I. There is some variation in this number as can be seen from the standard deviation (0.0031%) and range between the different percentiles. The 5% percentile shows a percentage quoted half-spread of 0.0055%, whereas the upper 95% percentile shows a half-spread of 1.47%.

The percentage effective half-spread is considerably lower than the quoted spread at an average of 0.0053%. This suggests that a considerable amount of trades occur within the quoted spreads. Again, we observe some variation in these spreads with a range from 0.0036% to 0.0084% for the 5% and 95% percentile, respectively.

The ratio of effective half-spread relative to quoted half-spread shows that trades occur at a value of about 66% of the quoted spread; hence, the effective cost of trading is about two-thirds of the quoted prices. This percentage has a range of about 54% to 76% for the 5% and 95% percentile, respectively.[8]

To provide more details on the evolution of the percentage quoted and effective spread, and the ratio of effective over quoted spread over time, we show a time series plot of weekly averages in Figure 4. In Panel A, we show the dynamics of the percentage quoted and effective spread over time. As can be seen from this graph, both the effective and quoted spreads peak in the early part of the sample at the time of the burst of the dot-com bubble. After this, we observe that both spreads decline, though quoted spreads decline at a faster rate up to the onset of the global financial crisis, when we observe increases in both spread measures. In Panel B, we plot the ratio of effective over quoted spread. We observe that over time this ratio has increased slowly from the start of our sample period to early 2007. The ratio drops sharply in 2008 and 2010.

From Figures 4 and 2, we observe that the spread measures increase in times of high volatility, whereas the ratio of the effective to quoted spreads seems to decrease. To formally assess whether there is a relation between the percentage quoted and effective spread and the ratio of effective to quoted spread and the IVI, we run regressions of these variables on the IVI and report results in Table III, where Newey–West corrected *T*-statistics are reported in parentheses. These regressions show that there is a strong positive relation between the

[8]Note that Madhavan et al. (1997) estimate the ratio of effective spread over implied spread to be between 0.5 and 0.6 for individual stocks traded on the NYSE in 1990. Our results are slightly higher and may be due to the fact that we evaluate the futures contracts traded in an electronic environment, whereas the Madhavan et al. study was conducted in a time when the NYSE used specialists and prices in fractions.

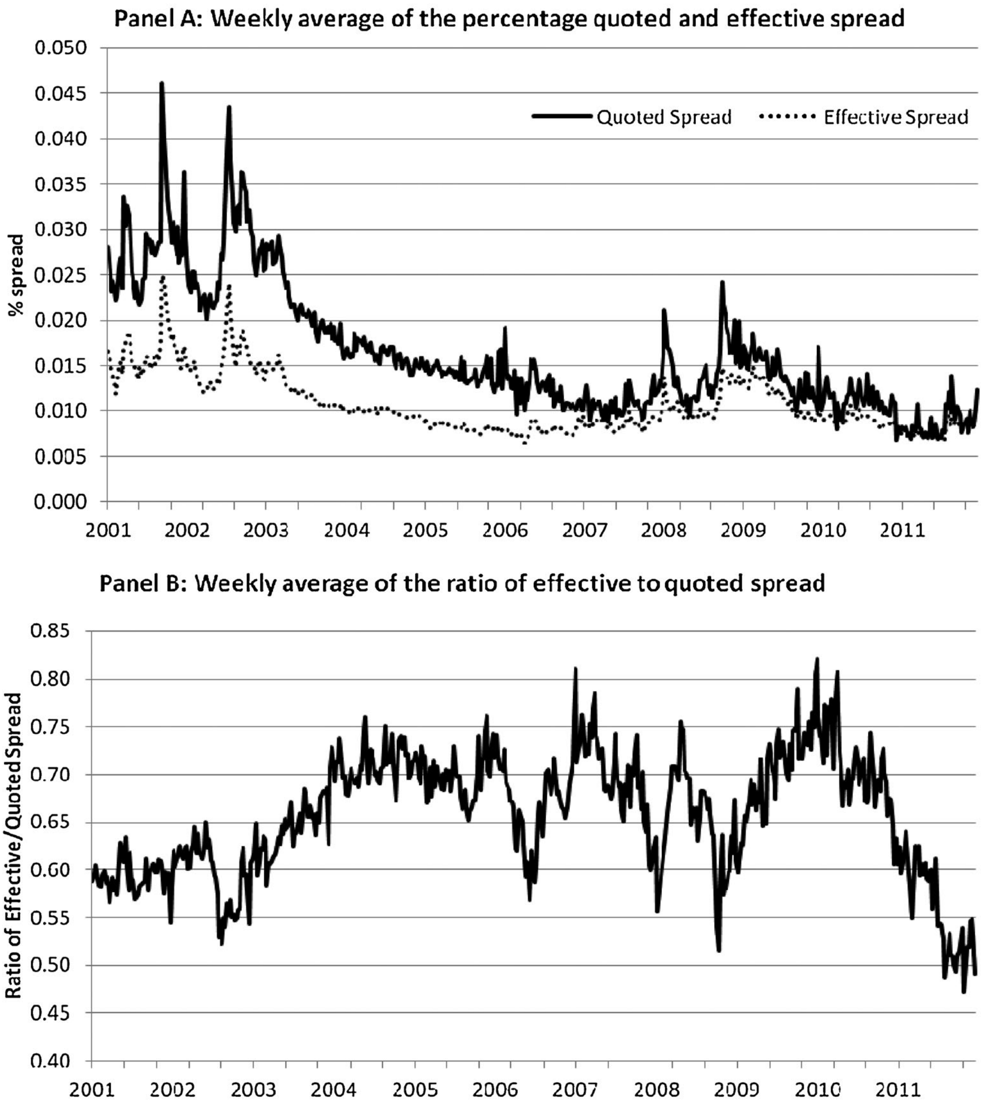

FIGURE 4
Weekly average of spread measures.
Note: This figure shows the percentage quoted and effective spreads (Panel A) and the ratio of the effective to quoted spread (Panel B) over the period of 2001–2011.

percentage quoted and effective spreads and the IVI, suggesting that both spreads increase in times of high volatility. In terms of economic significance, a one standard deviation increase in the IVI results in the quoted and effective spreads increasing by 0.0036 and 0.0017, respectively. The results also indicate a significantly negative relation between the ratio of effective to quoted spreads and implied volatility.

The positive relation between the spread and volatility has been reported in Stoll (2000, 2003) and Madhavan (2000) for stocks and Wang and Yau (2000) for futures, among many other studies. As discussed in prior research, the three components of the quoted spread, namely, asymmetry information, inventory cost, and order processing cost (Stoll, 1989), are all positively related to price volatility.

TABLE III
Regression Results for Spread Measures on the Implied Volatility Index

	Constant	*IVI* ($\times 10^{-3}$)	R^2
%QS	0.00830 (13.31)	0.382 (11.86)	0.3604
%ES	0.00664 (20.09)	0.186 (10.84)	0.3092
ES/QS	0.726 (132.28)	−3.15 (−12.51)	0.1931

Note. This table presents the regression results for spread measures on the implied volatility index (IVI). *%QS* is the percentage quoted spread, *%ES* is the percentage effective spread and *ES/QS* is the ratio of effective to quoted spread. *T*-statistics are robust for heteroskedasticity and autocorrelations (Newey & West, 1987) and are reported in parentheses. We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

Our results show that whereas both the quoted and effective spreads increase with volatility, the increase in the effective spread is lower than the increase in the quoted spread, resulting in a negative relation between the ratio of effective to quote spreads and volatility. These results suggest that during volatile periods, price improvement (or the difference between the quoted and effective spreads) is not adversely affected. If the trade is at the bid or ask with no price improvement, the quoted and effective spreads are the same. "The process of achieving price improvement is for the dealer to guarantee the current price and seek to better it" (Stoll, 2003). The dealer has a short-term option to step ahead of the prevailing order by providing a lower (higher) ask (bid) or to let the incoming market order trade against the prevailing order. Stoll (2003) and Ready (1999) note that the dealer will be more willing to step ahead if the incoming order is uninformed, leading to a price improvement. Therefore, if uninformed or noise trading increases during the volatile periods, the effective spread will not increase as much as the quoted spread.

4.1.2.. Time Effects and Efficient Price Innovations

In Table IV, we report summary statistics for the duration parameters and the innovations in the efficient price. The first column reports results for the duration parameters for trades. The average parameter value is 0.067. Although the average is statistically significant, it is close to

TABLE IV
Summary Statistics for the Duration Parameters and Efficient Price Innovations

	δ^{TRADE}	δ^{QUOTE}	σ^{TRADE}	σ^{QUOTE}
Mean	0.0666	−0.2756	0.0082	0.0029
T-stat	(11.81)	(−7.19)	(41.09)	(27.67)
SD	0.1414	1.5201	0.0037	0.0019
5th	−0.0880	−1.4222	0.0039	0.0003
25th	−0.0260	−0.1162	0.0055	0.0015
50th	0.0435	0.0461	0.0071	0.0024
75th	0.1477	0.1654	0.0101	0.0040
95th	0.2939	0.4847	0.0152	0.0067

Note. This table provides summary statistics on the duration parameters for trades and quotes, and for the innovations in the efficient price due to trades and quotes. *T*-statistics are computed for the daily estimates and are robust for heteroskedasticity and autocorrelations (Newey & West, 1987). We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

zero, suggesting that the duration between trades has little impact on the information of the trade and is very much in line with the innovations due to trades evolving in tick time (see Clark, 1973). From the distribution of the parameter estimates, we observe that the range of estimates is quite narrow around zero, with values at the 5th percentile of -0.088 and at the 95th percentile of 0.294. This suggests that the hypothesis for the duration parameter for trades to be equal to 0.5 can easily be rejected.

To gain more insight into the impact of time on the innovation in the efficient price, we show the magnitude of the innovation in the efficient price due to trades as a function of time in Figure 5, Panel A. As can be seen from this graph, there is a small and positive effect of time

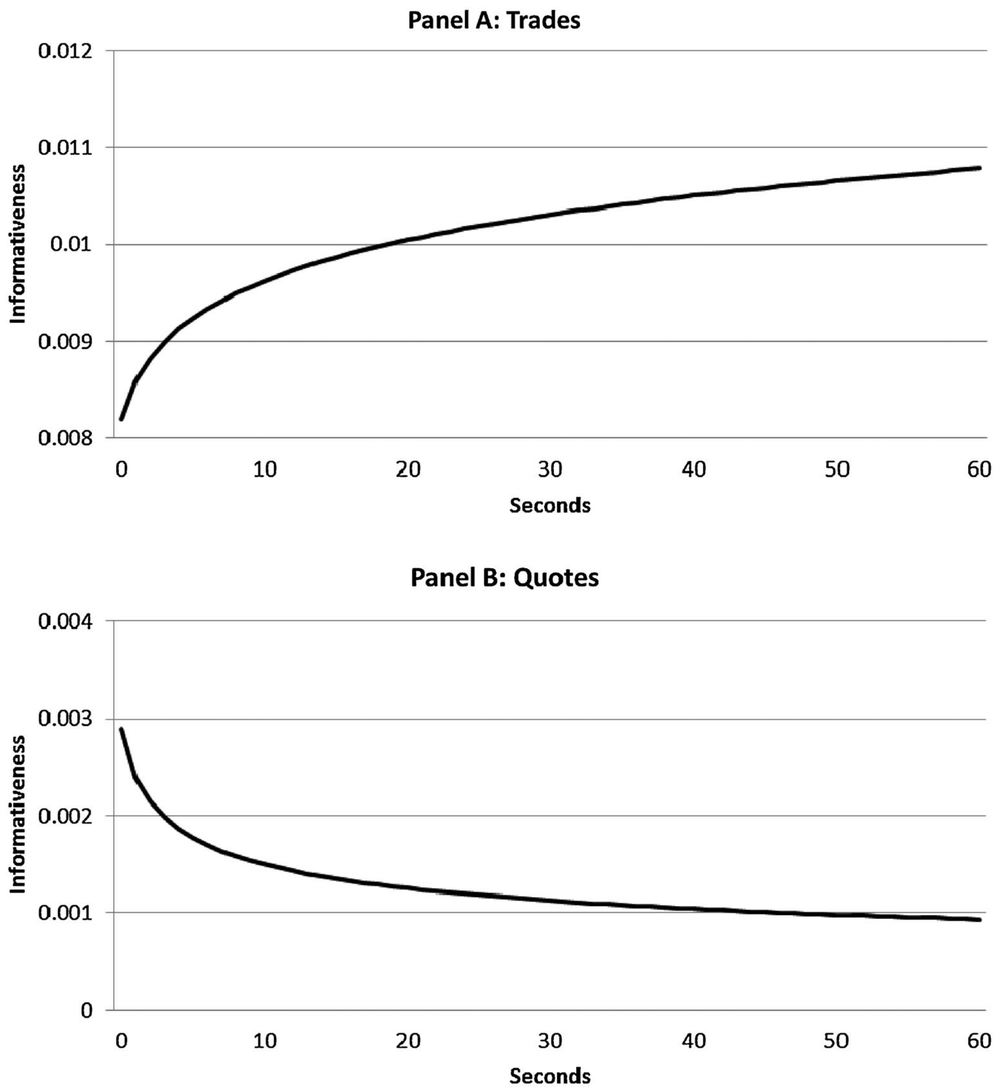

FIGURE 5

The impact of time on the innovation in the efficient price.

Note: This figure shows the effect of time (duration) on the innovations in the efficient price due to trades (Panel A) and quotes (Panel B). The x-axis shows durations in seconds. The y-axis shows the magnitude of the innovations in the efficient price due to trades (Panel A) and quotes (Panel B).

on the informativeness of trades. The increase in informativeness is largest for trades at relatively short durations. In particular, trades with a duration of 10 seconds see an increase in the impact of trades on the efficient price of 17.3% relative to trades that occur within the same second, while trades with a duration of 60 seconds see an increase in informativeness of 31.5%.

The second column of Table IV reports the results for the duration parameter of the quote process. We observe that, on average, this parameter is negative and significant. However, as can be seen from the percentiles, the median is close to zero, and the negative mean is driven by some large negative values for δ^{QUOTE}. From these statistics we can again reject the notion of the process evolving in calendar time and based on either median or mean, we can conclude that the process evolves in tick time or less than tick time.

Figure 5, Panel B, shows the effect of time on the informativeness of quotes. As shown in the figure, the informativeness of quotes decreases rapidly as durations increase. For a difference of 10 (60) seconds between quote innovations we observe a decrease in the informativeness of quotes of 48.4% (67.8%). This suggests that quote innovations are less informative during tranquil periods when the duration between quotes is long and quote innovations are more informative during more active periods with short durations.

The last two columns of Table IV show the results of the magnitude of the innovations in the efficient price, σ^{TRADE} and σ^{QUOTE}, for trades and quote innovations, respectively. We find that innovations due to trades are significant and about three times the impact of quotes on the efficient price (0.0082 vs. 0.0029). Given that trades reflect the private information in the market, this shows that there is significant private information in the market. The innovation due to quote changes is also statistically significant, but is considerably smaller than the impact of buys and sells, suggesting that the occurrence of trades is more informative than innovations in quotes.

4.2. Daily Aggregation

The results of the informativeness of trades and quotes presented in the previous section show that trades are more informative than quotes and that there is a considerable amount of private information in the FTSE 100 index futures contracts. However, as observed from Panel A of Table I, there are nearly twice as many quote innovations as there are trades within a day. In this section, we therefore aggregate the impacts of trades and quotes at a daily level to determine how much of the daily variability in the FTSE 100 index futures is due to trades and quotes.

We examine the contributions of trades and quotes to the daily variance of the efficient price, by computing daily variance ratios as follows:

$$\begin{aligned} VR_n^{TRADE} &= \frac{\sum_{l=1}^{L} \tau_{TRADE,l}^{2\delta^{TRADE}} \sigma^{2,TRADE} D_l^{TRADE}}{\sum_{l=1}^{L} \sigma_l^2}, \\ VR_n^{QUOTE} &= \frac{\sum_{l=1}^{L} \tau_{QUOTE,l}^{2\delta^{QUOTE}} \sigma^{2,QUOTE} D_l^{QUOTE}}{\sum_{l=1}^{L} \sigma_l^2}, \end{aligned} \tag{8}$$

where VR_n^{TRADE} is the ratio of the contribution of trades to the innovation in the efficient price, relative to the total innovation in the efficient price on day t, and VR_n^{QUOTE} is the contribution of quotes to the innovation in the efficient price relative to the total innovation in the efficient price on day t. Note that these definitions are similar to those of Hasbrouck (1991a, 1991b) and Chng (2004).

In Table V, we present the results for the two variance ratios. For the whole sample reported in Panel A, we observe that trades contribute most to the innovation in the efficient price, about 82%. This suggests that, on a daily basis, trades are highly informative about the underlying efficient price process. This finding is in line with results reported by Holmes and Tomsett (2004) and Chng (2004). Holmes and Tomsett report an average informativeness of 92% of trades for the open outcry trading environment and Chng reports an overall informativeness of trades of 80% in the screen-based trading environment.

To provide a more detailed view of the time-variation in the variance contributions of trades, we plot the weekly averages over time in Figure 6. From this graph, we can see that

TABLE V
Variance Ratios of Trades and Quotes

	Trade	*Quote*
Mean	82.45%	17.55%
T-stat	(141.66)	(30.15)
SD	11.45%	11.45%
5th	60.52%	0.71%
25th	76.06%	8.69%
50th	83.54%	16.46%
75th	91.31%	23.94%
95th	99.29%	39.48%

Note. This table presents summary statistics for the variance ratios of trades and quotes as computed in Equation (8). *T*-statistics are computed for the daily estimates and are robust for heteroskedasticity and autocorrelations (Newey & West, 1987). We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

FIGURE 6
Weekly average of the variance contribution of trades.
Note: This figure shows the weekly average of the variance contribution of trades over the period of 2001–2011.

there was an upward trend in the variance contribution of trades in the early part of the sample up to the end of 2006. From that point onwards there was a sharp decline in the variance contribution of trades, which reached a low point toward the end of 2008. After this there was again a sharp increase in the variance contribution up to early 2010, after which the variance contribution dropped substantially.

The troughs observed in the graphs seem to align with the crisis periods and with periods of high volatility. To assess the relationship between the variance contribution of trades and volatility, we run a regression of the variance contribution of trades on the IVI, where we report Newey–West adjusted T-statistics in parentheses:

$$VR_n^{TRADE} = \underset{(122.48)}{0.984} \quad \underset{(-18.50)}{-7.254 \times 10^{-3}\mathrm{IVI}_n} \qquad R^2 = 38.06\%.$$

As can be seen from the regression results, there is a highly significant negative relation between the variance contribution of trades and the IVI. In economic terms, a one standard deviation increase in the IVI leads to a decrease in the variance ratio due to trades of 6.78%. This shows that the variance contribution of trades is lower in times of high volatility.

The regression results support the hypothesis that noise trading increases market volatility and, accordingly, decreases trade informativeness. De Long, Bradford, Shleifer, Summers, and Waldmann (1990a, 1990b) provide one of the first models to show how noise traders not acting on information can affect prices in a systematic way. Acting on sentiments or liquidity needs and trading in concert, noise traders can cause prices to deviate from intrinsic values. This additional source of risk is reflected by the higher volatility caused by noise traders.

It is worth noting that the positive relation between noise trading and volatility (or correspondingly, the negative relation between trade informativeness and volatility) reported here is consistent with our previous results concerning the quoted and effective spreads. As mentioned above, if noise trading increases during volatile periods, the effective spread will not increase as much as the quoted spread.

4.3. The Effect of Size on the Informativeness of Trades and Quotes

The next question we address is whether the informativeness of trades and quotes is affected by size. There is considerable literature on the role of size (volume) in trades. Several studies suggest that medium-sized trades are most informative (e.g., Chakravarti, 2001), whereas others document that larger trades are more informative for some stocks (Easley, Kiefer, & O'Hara, 1997). However, there is less evidence on the role of size in quotes (i.e., whether inside quotes are more or less informative if these quotes are for large volumes).

In this section, we estimate an extended version of the model developed in Section 2. Specifically, we modify Equation (4) by introducing separate parameters to capture the impact of trade and quote size on the innovation in the efficient price, that is,

$$\begin{aligned}\sigma_l = {} & \tau_{TRADE,l}^{\delta^{TRADE}}(\sigma^{SMALLTRADE}D_l^{SMALLTRADE} + \sigma^{MEDTRADE}D_l^{MEDTRADE} + \sigma^{LARGETRADE}D_l^{LARGETRADE}) \\ & + \tau_{QUOTE,l}^{\delta^{QUOTE}}(\sigma^{SMALLQUOTE}D_l^{SMALLQUOTE} + \sigma^{MEDQUOTE}D_l^{MEDQUOTE} + \sigma^{LARGEQUOTE}D_l^{LARGEQUOTE}),\end{aligned} \tag{9}$$

where *SMALL*, *MED*, and *LARGE* describe the effects of small-, medium-, or large-sized trades or quote innovations.

In Table VI, we present a breakdown of the percentages of trades and quotes for different sizes. The first column shows the breakdown for trades. We observe that the majority of trades (around 77%) are for a single contract. Beyond trades for a single contract we observe that volume decreases nearly monotonically, with 14.8% of trades being for between two and five contracts and 8.02% of trades being for more than five contracts.

The second column of Table VI shows the breakdown of volumes for quotes. We find that 79.1% of the quotes for FTSE 100 index futures are for a single contract. Again, we observe a nearly monotonic decline after this. Quotes for volumes between two and five contracts represent 8.88% of the sample and quotes for more than five contracts represent 12.04% of the sample.

Based on the observation in Table VI, we define *SMALL* as trades and quote innovation for one contract (most trades and quote innovations have size of one contract); *MED* as trades and quote innovation with a size between 2 and 5; and *LARGE* as trades and quote innovations with a size greater than 5.

In Table VII, we present the results for the parameter estimates for the impact of trades and quotes of different sizes on the efficient price process. The first three columns show the contributions of trades to the efficient price. Considering the means of these coefficients, we observe that large trades ($\sigma^{LARGETRADE} = 0.0113$) are considerably more informative than medium- (0.0079) or small-sized (0.0072) trades.[9] This is observed consistently through the distribution of the parameter estimates.

TABLE VI
Distribution of Trade and Quote Sizes

Trade or quote size	*Trade (%)*	*Quotes (%)*
1	77.23	79.08
2	6.53	3.50
3	3.58	2.09
4	2.58	1.64
5	2.07	1.65
6	1.37	1.16
7	0.94	1.02
8	0.83	0.93
9	0.61	0.83
10	0.73	0.91
>10	3.55	7.18
2 to 5	14.76	8.88
>5	8.02	12.04

Note. This table presents the percentages of trades and quotes for different sizes. We present percentages up to volumes of 10 contracts, and for volumes between 2 to 5 and greater than 5.

[9]We have conducted tests for the difference in means of these estimates. All tests (not reported) show that these differences are statistically significant. We have also performed a robustness test by constructing the size specifications based on different cut-off point, where small trades are for a volume of 1 and 2 contracts, medium trades for a volume of 3 to 6 contracts and large trades represent a volume of more than 6 contracts. The interpretations of the results (available upon request) are similar to those reported in Table VII.

TABLE VII
Impact of Trades and Quotes of Different Sizes on the Efficient Price

	$\sigma^{SMALLTRADE}$	$\sigma^{MEDTRADE}$	$\sigma^{LARGETRADE}$	$\sigma^{SMALLQUOTE}$	$\sigma^{MEDQUOTE}$	$\sigma^{LARGEQUOTE}$
Mean	0.0072	0.0079	0.0113	0.0025	0.0033	0.0029
T-Stat	(37.60)	(41.49)	(51.64)	(21.58)	(27.97)	(29.44)
SD	0.0036	0.0036	0.0046	0.0024	0.0025	0.0021
5th	0.0030	0.0036	0.0058	0.0000	0.0000	0.0000
25th	0.0044	0.0053	0.0079	0.0000	0.0015	0.0016
50th	0.0064	0.0069	0.0100	0.0022	0.0030	0.0027
75th	0.0090	0.0098	0.0141	0.0039	0.0046	0.0041
95th	0.0140	0.0147	0.0196	0.0067	0.0078	0.0067

Note. This table provides summary statistics on the parameters for the innovations in the efficient price due to trades and quotes of different sizes. *T*-statistics are computed for the daily estimates and are robust for heteroskedasticity and autocorrelations (Newey & West, 1987). We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

In the NYSE, the "stealth-trading" hypothesis of Barclay, Dunbar, and Warner (1993) argues that medium-sized trades are more informative and move stock prices more than small and large trades. The reason is that informed traders realize that large trades could give them away and small trades have higher transaction costs. See also Chakravarti (2001). In contrast, the electronic trading system of LIFFE facilitates informed traders to execute large trades because of immediate and anonymous trade execution. Therefore, large trades of FTSE futures are more informative than small and medium trades.

The last three columns report the contributions of quote innovations to the efficient price for quotes of different sizes. As we have noted previously, quotes are considerably less informative than trades. We also note that medium-sized quotes ($\sigma^{MEDQUOTE} = 0.0033$) contribute marginally more to the innovation in the efficient price process than large quotes (0.0029) and quotes for a single contract (0.0025).

Since trades and quotes for different sizes have different frequencies of occurring within a day, we again compute variance ratios, but now for trades and quotes at different sizes. The results reported in Table VIII confirm the observation from Table VII and show that on a daily aggregated level, large trades contribute most to the efficient price process, 36% on average. This means that of the daily variability in the efficient price, 36% comes from large trades. Medium and small trades contribute about 27% and 17%, respectively. The sum of the percentages of trades at different sizes again shows that trades contribute most to the daily variance of the efficient price process, the variance ratios for trades add up to about 80% on average, suggesting that trades are highly informative.

Examining the overall variance ratios for quotes, we observe that the ratios do not change much across different sizes. Medium-sized quotes contribute 7.5% to the daily variance of the efficient price, followed by large quotes at 6.6% and small quotes at 5.7%.

We examine the time variation in the variance contributions due to trades and quotes in Figure 7. Panel A shows the results for small, medium, and large trades and Panel B shows the results for quotes. The two panels generally illustrate that all the trade and quote time series do not show much variation, hovering between zero and 0.3. The exception is the large trade series with a wider range from 0.15 to 0.68. The pattern of the large trade series is similar to that of Figure 6, an increasing trend for the period of 2001–2006 with two troughs during the volatile periods of 2008 and 2010. This confirms the results that large trades are more

TABLE VIII
Variance Ratios for Trades and Quotes of Different Size

	$VR^{SMALLTRADE}$	$VR^{MEDTRADE}$	$VR^{LARGETRADE}$	$VR^{SMALLQUOTE}$	$VR^{MEDQUOTE}$	$VR^{LARGEQUOTE}$
Mean	17.14%	27.16%	35.77%	5.73%	7.57%	6.63%
T-stat	(65.17)	(119.71)	(58.98)	(16.98)	(27.77)	(38.68)
SD	6.33%	6.72%	12.78%	8.09%	7.64%	6.02%
5th	6.93%	14.46%	17.20%	0.00%	0.00%	0.00%
25th	12.70%	23.56%	25.82%	0.00%	1.83%	2.43%
50th	17.05%	28.40%	35.87%	2.71%	6.35%	6.01%
75th	21.46%	31.46%	43.76%	8.16%	11.10%	9.30%
95th	27.30%	36.67%	58.00%	22.08%	19.26%	15.71%

Note. This table presents summary statistics for the Variance Ratios of trades and quotes for the extended model as shown in Equation (9). *T*-statistics are computed for the daily estimates and are robust for heteroskedasticity and autocorrelations (Newey & West, 1987). We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

informative than small and medium trades and the variation of variance contribution of trades over time is associated with large trades.

An interesting issue is why the variance contribution drops during the volatile periods for large trades but not for smaller trades. Lee and Radhakrishna (2000) find that large trades in the US stocks are mostly institutional trades. We assume the same situation for FTSE index futures. Sias (1996), for example, report a positive relation between stock volatility and institutional holdings. Gabaix, Gopikrishnan, Plerou, and Stantley (2006) present a model in which volatility is caused by the large trades of institutional investors. Sias argues that institutional investors who tend to trade in large volume may engage in noise trading. An

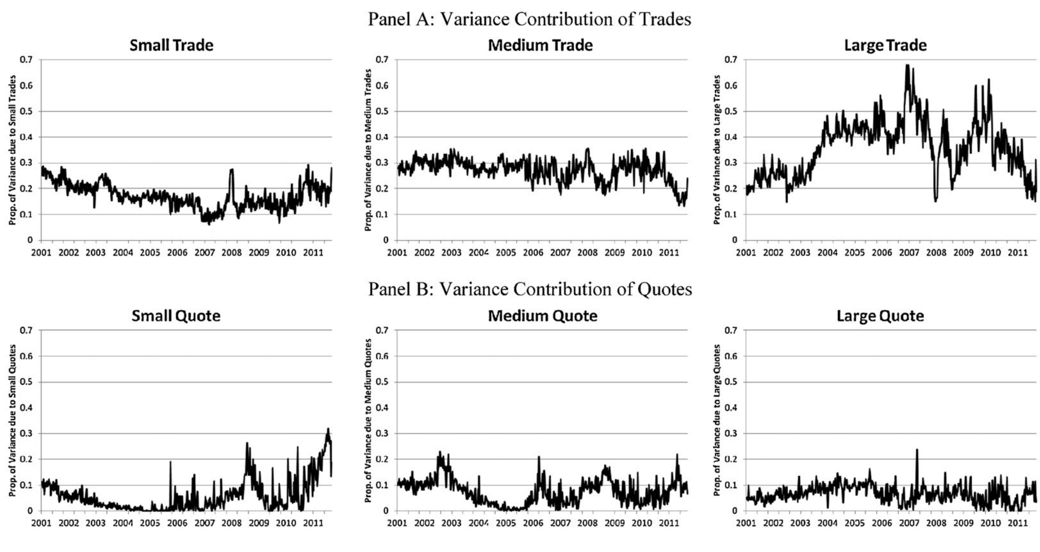

FIGURE 7
Weekly average of the variance contribution of trades and quotes of different sizes.
Note: This figure shows the weekly average of variance contributions of trades (Panel A) and quotes (Panel B) of different sizes over the period of 2001–2011.

TABLE IX
Regression Results for Variance Contributions on the Implied Volatility Index

	Constant	*IVI* ($\times 10^{-3}$)	R^2
$VR_{SMALLTRADE}$	0.154 (27.28)	0.790 (3.35)	0.0156
$VR_{MEDTRADE}$	0.285 (50.46)	−0.588 (−2.09)	0.0077
$VR_{LARGETRADE}$	0.495 (42.52)	−6.162 (−13.12)	0.227
$VR_{SMALLQUOTE}$	−0.0065 (−1.10)	2.896 (9.67)	0.121
$VR_{MEDQUOTE}$	0.0031 (0.61)	3.230 (13.95)	0.200
$VR_{LARGEQUOTE}$	0.069 (16.25)	−0.167 (−1.07)	0.0008

Note. This table presents the regression results for variance contributions of trades and quotes of different sizes on the implied volatility index (IVI). $VR_{SMALLTRADE}$ is the variance contribution due to small trades, $VR_{MEDTRADE}$ is the variance contribution due to medium trades, and $VR_{LARGETRADE}$ is the variance contribution due to large trades. Likewise, $VR_{SMALLQUOTE}$ is the variance contribution due to small quotes, $VR_{MEDQUOTE}$ is the variance contribution due to medium quotes, and $VR_{LARGEQUOTE}$ is the variance contribution due to large quotes. *T*-statistics are robust for heteroskedasticity and autocorrelations (Newey & West, 1987) and are reported in parentheses. We use an automatic lag length selection formula based on a Bartlett Kernel, that is, $floor(4(T/100)^{2/9})$ to compute the lag length standard error correction.

uninformed institutional investor may trade to convey a (feigned) signal to clients that he/she is informed (Truemann, 1988). Sias also provides different reasons why institutional investors are also more prone to herding bias than individual investors. Such behavioral bias will increase price volatility and aggravate price informativeness. In particular to index futures, during volatile periods, institutional investors may trade more for uninformed hedging.

Our results support the positive relation between institutional investors and noise (or uninformed) trading when the market is volatile. However, we should point out that many studies, for example, Cohen, Gompers, and Vuolteenaho (2002) and Barber and Odean (2008), have found a stabilizing impact of institutional investors on stock prices.

Finally, as we observe a negative relation between the variance contribution due to trades and the IVI, we examine whether the informativeness of trades and quotes of different sizes is related to the level of market volatility (measured by the IVI). We report results for this regression in Table IX. When we consider the results for the variance contributions due to trades, as expected, we find a significant and negative relation between the variance contribution due to large trades and volatility with a R^2 of 22.7%. We also observe a positive (negative) relation between the variance contribution due to small (medium) trades and the IVI; however, we are cautious about the interpretation of the results because of a small value of R^2 of about 1%.

For quotes, we observe that there is a positive and significant relation between small and medium quotes, and implied volatility, implying that these quotes become more informative in times of high volatility. We observe no significant relation for large quotes. Nevertheless, we should focus on the results of variance contributions from trades because we have shown that trades contribute the majority (80%) of the innovation to the efficient price.

5. CONCLUSIONS

There are two opposing views on the informativeness of trades in index futures contracts. On the one hand, index contract trades can be expected to be less informative as the underlying is a basket of securities and any private information on specific securities in the basket is diversified away. This view suggests that the trades in index products are mainly by noise traders. On the other hand, trades in index futures can be expected to attract informed traders, when these markets complete the cash market and improve market depth.

In this study, we examine the informativeness of trades in the FTSE 100 index futures contract. Using a tick time model similar to Frijns (2006), we decompose the innovation in the efficient price into an innovation due to trades and an innovation due to quotes. We estimate this model on a daily basis over an extensive time period from 2001 through 2011. We find that trades are highly informative, contributing about 80% of the innovation in the efficient price. These findings are important as they suggest that index futures markets contain valuable information and complete the underlying cash market. We observe that the informativeness of trades has increased over time, yet we notice two considerable drops during the recent global financial crisis and the European debt crisis. We also find a negative relationship between the informativeness and market volatility. The overall results show that noise traders are more active during volatile and crisis periods.

When we decompose the innovation in the efficient price due to trades and quotes into different size groups, we find that large trades are more informative than smaller trades. Price informativeness over time is primarily determined by large trades and prices are less informative during volatile periods.

Our model also provides estimates for the quoted and effective half-spread, and the impact of time (duration between trades and quote innovation) on the informativeness of trades and quotes. We observe that both quoted and effective spreads have decreased considerably over time and the spreads increase with volatility. However, the increase in the quoted spread is larger than that of the effective spread during volatile periods, suggesting that the price improvement process by the dealer is not adversely affected. In addition, we observe that time has only a minor impact on the informativeness of trades, but quote innovations lose their informativeness when durations increase.

Our results have important implications. They show that most trades in the FTSE 100 index futures contracts are initiated by informed traders and not by noise traders. The results indicate a connection between noise or uninformed trading and volatility. Considering that large trades are mostly institutional trades, the overall results also support the positive relation between institutional investors and uninformed trading (including hedging) during volatile periods.

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