The impact of post-trade transparency: evidence from an emerging stock market

Abstract

This study examines the impact of greater post-trade transparency on efficiency and price discovery and the interaction between them after changes due to a specific event. We find increased efficiency for both large and small firms, though the impact on stock prices is greater when the firm is larger. In addition, it is found that trading reveals more private information for large firms and generally more public information for small firms, though no evidence of an interaction between changes in efficiency and price discovery brought on by the event is found. The results imply that greater transparency does convey stock price information to investors faster, ultimately driving large firm stocks toward a strong form-efficient market; a semi-strong form-efficient market for the small firms; however, the change in efficiency does not further stimulate price discovery. Our findings support the view that greater transparency has a positive impact on market quality.

Keywords: transparency; opening of limit-order books; efficiency; trade-related standard deviation; quote-related standard deviation; price discovery.
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1. Introduction

Transparency refers to what and how much information market participants should have during the trading process. The heart of the debate about transparency lies in fairness for various investors, inter-market competition, and the speed and precision by which new information is reflected in the stock price. There are two different dimensions to transparency: pre-trade and post-trade. Pre-trade transparency refers to the dissemination of prices and orders before a trade occurs, while post-trade transparency refers to public and timely disclosure of the limit-order books after a trade has been made. Most of the existing literature focuses on the impact of pre-trade transparency\(^1\) with little focus on the issues encountered by post-trade transparency, perhaps to a lack of real data or events that create change. In this study, we investigate the effect of an event leading to greater transparency on market quality in a fully electronic, automated, and order-driven market.

Beginning on January 2, 2003, a change in rules in the Taiwan Stock Exchange (TSEC) requires that information about another four best bids/asks, as well as the original best bid/ask, with orders be disclosed. Therefore, information for a total of five best bids/asks with the corresponding unexecuted orders is publicly disseminated to all investors after each trading. This rule change applies to all stocks traded on the TSEC. In these special circumstances, we are able to examine how greater post-trade transparency impacts market quality. Specifically, we investigate the effects of greater post-trade transparency on efficiency, price discovery, and the interaction of these changes using the same stocks within the same market structure. Efficiency is critical in the financial market in terms of incorporation of accurate information into the stock price (Fama, 1970), while price discovery is one of the most important functions of asset pricing (O’Hara, 2003). Transparency plays a central role in both of these

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\(^1\) See, for example, Bloomfield and O’Hara (1999), Flood et al. (1999), Madhavan et al. (2005), Boehmer et al. (2005), Baruch (2005), Cao et al. (2009), Boulatov and Thomas (2013), and Tang (2014), etc.
processes. This study enriches the existing literature on post-trade transparency.

Theoretical studies related to the topic of transparency in the marketplace include those by Admati and Pfleiderer (1991), Paul (1993), Madhavan (1995, 1996), Baruch (2005), Frutos and Manzano (2005, 2014), Boulatov and George (2013), Han and Yang (2013), and Tang (2014), to name a few. These studies have found that transparency does affect trading cost, stock liquidity, return volatility, and price informativeness, though the effects are mixed. Empirical studies include those by Board and Sutcliffe (1996), Gemmill (1996), Porter and Weaver (1998), Bloomfield and O’Hara (1999), Flood et al. (1999), Boehmer et al. (2005), Madhavan et al. (2005), Cao et al. (2009), and Riordan and Storkenmaier (2012). It has been found that transparency matters, but the effects are complicated. There is little agreement in theoretical and empirical studies on the impact of transparency on market quality. However, most regulators, such as the U.S. Security and Exchange Commission (1994) and U.K. Office of Fair Trading (1994), for example, believe that greater transparency will improve market quality and result in greater efficiency and fairness.

Although this study is based on a large body of research investigating how transparency impacts market quality, there are important differences between this current and past work. First, there is little in the literature (see footnote 2) on post-trade transparency. The primary focus of post-trade transparency in the past has been the reduced reporting latency of a trade (Porter and Weaver, 1998; Riordan and Storkenmaier, 2012). By contrast, this study investigates the impact of increased dissemination of information on unexecuted bids/asks with orders after each trade. In essence, this is a post-trade disclosure of limit order books. Second, post-trade information for the five best bids/asks and their corresponding orders is kept until the next trade happens, forming a useful reference for investors interested in their next trade. Traditionally, empirical transparency studies have focused on the issues of trading cost, liquidity, price volatility, and price informativeness. This study investigates the issues of efficiency, price discovery, and the interaction of changes and uses real transactional data for an empirical study (as opposed to simulated experimental data) in the process. Although experimental studies, such as those by

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2 The existing literature examining post-trade transparency includes studies by Board and Sutcliffe (1996), Gemmill (1996), Porter and Weaver (1998), Frutos and Manzano (2005), Riordan and Storkenmaier (2012), etc.
Bloomfield and O’Hara (1999), Flood et al. (1999), and Bloomfield et al. (2015) are valuable, the results obtained reflect a simplified design or model rather than real transactions.

This empirical study follows an exogenous and obvious change in a trading reporting system, specifically the TSEC’s opening of limit-order books to the public. This disclosure reformation was a pure microstructure event, not under the control of the firm’s management. Any alteration in market quality around this event is thus external, rather than arising from the impact of the leakage of inside information about a firm’s future prospects. This study contributes to the existing literature on transparency issues. Using the method detailed by Hasbrouck (1991b), we further decompose the price discovery into two components: trade-related standard deviation and quote-related standard deviation. Analyzing the change of individual components has important implications, and the effects of a greater transparency on differently sized firms are investigated. Madhavan (1996) pointed out that differently sized firms would react differently to varying transparency conditions. Hence, we categorize the sample firms into two equal groups according to their size or market capitalization and then examine the impact of transparency on differently sized firms. Given that efficiency and price discovery are related to asset pricing, any change in these around a specific event—such as the change in the TSEC—will give us a reference as to how transparency impacts stock price. The TSEC’s experience in opening of limit-order books is a blueprint for electronic, automated, and order-driven markets worldwide.

Our results show a significant decrease in the relative return dispersion (RRD), lag response, and firm-specific noise for both large and small firms after the event. This outcome implies that there would be fewer pricing errors and that stock prices would adjust more promptly to changes in market information. In a word, there was an increase in efficiency after the rule change. Regarding the components of price discovery, there is an increase in trade-related standard deviation for large firms and an increase in quote-related standard deviation for small firms. This means that trading reveals more private information for large firms and more public information for small firms. These results indicate that the change in transparency forces large firms toward a strong form-efficient market while promoting semi-strong form efficiency for small firms. Finally, we find no interaction between efficiency and price
discovery due to the greater transparency event. All in all, this study’s findings are consistent with the arguments that transparency promotes efficiency and accelerates the stock price toward its true value. The opening up of the limit-order books allows investors to learn more information about trade patterns, the existence of order imbalances, and more at a faster pace. In a more transparent market, investors are able to set stock prices more efficiently and accurately. Our study supports the viewpoints that transparency matters in the sense that it has a positive impact on efficiency and the components of price discovery. Our results are also consistent with the arguments of Pagano and Roell (1996), Bloomfield and O’Hara (1999), and Flood et al. (1997b).

The remainder of the paper is organized as follows: Section 2 gives a description of the TSEC; Section 3 discusses data sources, sampling methodology and sample point filtering; Section 4 describes the hypotheses to be tested in this study; Section 5 describes and explains the research methodology. The empirical results and their economic meanings are provided in Section 6, and some conclusions are offered in the final section.

2. Institutional Description of the TSEC

The TSEC is a pure order-driven market with no designated market makers, specialists, or dealers. Essentially, it is a fully computerized trading system\(^3\). The TSEC trades five days (Monday-Friday) a week, except on national holidays, from 9:00 a.m. to 1:30 p.m. each day. Although investors can submit their orders to the system starting at 8:30 a.m., they are not executed until 9:00 a.m. Each day, the TSEC sets the stocks’ opening prices by matching the largest amount of bid and ask orders in the limit-order books. After the market opens, the trading rules are as follows: (1) the investors’ orders are matched in price, then time priority, and, after closing, unexecuted orders in the limit-order books are eliminated overnight; (2) the setting price in each call is where the largest shares can be traded; (3) all bid orders above the setting price and all ask orders below the setting price are executed. The unexecuted orders are kept in next call; (4) orders in limit-order books are batched over various time intervals, which are dependent on the trading situation. The average frequency is

\(^3\) The institutional description and the data in the next section are adapted from Lin et al. (2016), another paper from our team.
45 seconds for each trading cycle; (5) in the last five minutes (1:25-1:30), only one call is issued, and the setting price is the closing price for that day; (6) a price limit of ±10% from the previous trading day’s close price is imposed. The price limit rule is applied to the open price, closing price, and the transaction price that takes place in the middle of the trading session (9:00-13:25).

The January 2, 2003, event leading to the increase in transparency is a key institutional characteristic of the TSEC. Before this date, the TSEC disclosed only the transaction price, transaction volume, and the one and only best bid/ask after each trade, with orders from the limit-order books. Beginning from this date, the TSEC disclosed another four best bids/asks with orders. The TSEC officials argued that this change would promote transparency. In fact, the event made the TSEC one of the most transparent limit-order book markets in the world.

Individuals are the major investors on the TSEC. According to statistics from the TSEC’s annual reports, the percentage of trading volume by individuals to total market volume was 70% to 80% for the years 2002 and 2003, respectively. However, because of the opening of the market to foreign institutional investors, this percentage has gradually decreased. By 2014, the percentage fell to 58.80%, but the majority of punters are still individuals. Individual investors on the TSEC have limited ability to refer to factual information, often being affected by and letting their actions be directed by groundless rumors and sentiment. Thus, most of them are assumed to be uninformed or noise traders (Bange, 2000; Sias et al., 2006).

3. Data

In this study, real-time transaction data and daily data from the TSEC for the period from September 1, 2002, to April 30, 2003, are used. All data are retrieved from the Taiwan Economic Journal (TEJ) database. A number of criteria are used in selecting the data sample for this study; first, the firms listed on the TSEC must have survived from at least the end of 2001 to April 30, 2003. Second, observations where either the bid or ask prices are non-positive, or the difference between the ask price and the bid price is non-positive, are deleted. Third, we delete ticks that have had no trades.

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4 See TSEC’s Fact Book for 2003.
Fourth, those trades and quotes that have been time-stamped outside the regular TSEC trading time are also excluded. Fifth, overseas firms are not included in the sample.

Firms listed on the TSEC are sorted equally into three groups based on their 2001 year-end capitalization. The first group includes firms with the largest capitalization stocks, while the third is composed of firms with the smallest capitalization stocks. However, given that there is not a significant difference in the capitalization from one to the other, the second group is discarded. Then, the statistical simple random sampling approach is used to randomly select 100 firms from the first group and 100 firms from the third group for a total 200 firms in our sample. The first 100 sub-sample firms are called large firms, and the third 100 sub-sample firms are called small firms. The sample set includes 4,902,477 observations for the sample period. The firms in the sample, both large and small, are distributed across various industries listed on the TSEC and are fairly representative of the stock market.

The event day, when the TSEC began to disclose the best five bids/asks with orders in its limit-order books, is naturally January 2, 2003. The period, from September 1, 2002, to December 31, 2002, is called the estimation period (before the event); the period from January 1, 2003, to April 30, 2003, is called the event period (after the event). Until now, there has been no rule for determining the lengths of the estimation period and the event period. Our requirement is that the event must be obvious, well-known to investors, and not disturbed by other events. Fortunately, during our sample period, no other major events happened that affected the TSEC, allowing us to compare the market quality for the same stocks traded in the same market but with different post-transparency levels.

4. Hypotheses

How does transparency affect market quality? There has been no definitive answer to this question until now. One reason may be that the definitions of the sort and scope of transparency can be very different when corresponding to various investigations. In this section, some predictions and specific hypotheses that will be tested are outlined. It is a natural starting point to consider whether a greater transparency event impacts market efficiency. In the theoretical literature, Admati and Pfleiderer (1991) demonstrated that sunshine trading will increase the information
content of the price and market efficiency. Frutos and Manzano (2005, 2014) proved that trade disclosure raises the accuracy of traders’ expectations about a firm’s liquidation value and thus promotes price information efficiency. They also found that less information is impounded into a price in an opaque market, reducing transaction price efficiency. Baruch (2005) showed that more information is revealed by price in an open limit-order book situation. Madhavan et al. (2005) thought it was possible that informed traders would trade more accurately in a transparent system, speeding up the process of price discovery and efficiency. On the other hand, Paul (1993) and Han and Yang (2013) argued this free access to information might delay private information production, thereby harming market efficiency. Boulatov and Thomas (2013) argued that it is the hidden liquidity that attracts informed traders to trade, that the price discovery is faster, and that the market is more efficient in opaque markets if informational rents are shared among insiders. Given the inconsistency of predictions derived from theoretical frameworks for similar issues, the following hypothesis is tested:

**H1**: Disclosure of limit-order books has no effect on efficiency.

There are two opposing arguments in regards to the impact of transparency on price discovery; one is positive and the other is negative (Tang, 2014). From the positive viewpoint (O’Hara, 1995), it is thought that traders will re-estimate the true value of stocks and adjust their ordering behavior accordingly as more stock market information becomes available. The adjustment is continued until all available information is exhausted, and a new equilibrium is reached. In short, transparency in the market will force the price of a stock closer to its true value and improve price efficiency and price discovery. From the negative viewpoint, as pointed out by Flood et al. (1999) and Tang (2014), the disclosure of limit-order book information has the effect of “crowding out” the production of private information. In other words, disclosure reduces the expected benefits of becoming informed, which in turn discourages traders from searching for private information. Finally, disclosure decreases the amount of private information produced. When the positive influence dominates the negative one, disclosure is helpful for price discovery. Otherwise, disclosure is harmful. In addition, the components of price discovery, trade-related standard deviation, and quote-related standard deviation may be impacted differently
by the transparency event. These issues have not been investigated until now, despite their important implications. Based on these two opposing arguments about price discovery and price discovery’s important components, we arrive at the following hypotheses:

**H2a**: Disclosure of limit-order books has no effect on the trade-related standard deviation.

**H2b**: Disclosure of limit-order books has no effect on the quote-related standard deviation.

**H2c**: Disclosure of limit-order books has no effect on price discovery.

The last hypothesis that will be examined in this study is the co-movement or interaction between the changes in efficiency and price discovery, which are brought about by the disclosure of the limit-order books. In the existing literature (Barkham and Gelter, 1995) it is argued that price discovery would happen first in an efficient market and then be transferred to a less efficient one. To the best of our knowledge, there is no evidence in present literature on whether changes in efficiency and price discovery are positively or negatively correlated. Hence, the following hypothesis is tested:

**H3**: There is no interaction between changes in efficiency and price discovery.

The testing of these three hypotheses is discussed in the later sections.

5. Methodology

The measures of efficiency, the price discovery and the measures of its two components, and the methods used in this study are described below.

(1) Efficiency

Following Amihud et al. (1997), we use the dispersion of individual stock around market return to measure efficiency. For day t, the relative return dispersion is calculated by

\[ RRD_t = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_{it}^2, \]

where \( \varepsilon_{it} \) is the market model residual of stock i on day t, and n is the number of stocks. Other is equal; the differences in RRD between, before, and after the event indicate differences in efficiency due to the impact on transparency.

In the lag market model, there are two factors that may be used to measure
inefficiency (Amihud et al. (1997)): the lag response and the firm-specific noise. The lag market model is formulated as follows:

\[ R_{it} = \alpha_i + \beta_i R_{Mt} + 1 \beta_i R_{Mt-1} + \varepsilon_{it}, \]  

(2)

where \( R_{it} \) is the return for stock \( i \) at day \( t \); \( R_{Mt} \) and \( R_{Mt-1} \) indicate the market returns for day \( t \) and \( t-1 \), respectively; the coefficient \( 1\beta_i \) is called the lag response; and \( \varepsilon_{it} \) is the residual whose variance denoted by \( \text{var}(\varepsilon) \), which is a proxy for firm-specific noise. The model is estimated separately over the periods before and after the event.

(2) Price discovery

There are two methodologies commonly used to measure price discovery or efficient price change, both of which were developed by Hasbrouck in 1991b and then in 1995. The latter method involves observing information shares for a stock in various markets and uses a time series approach. In this study, Hasbrouck’s earlier model (1991b) is used to infer the components of price discovery surrounding the event of January 1, 2003. Following this model, all stock price movements are assigned to one of two categories: one is associated with trade (trade-related), and the other is unassociated with trade (quote-related). Following Hendershott et al. (2011), the price movements are considered to release private information if they are associated with trades; otherwise they are considered to reflect public information if they are orthogonal to trades. The full model is as follows5:

\[ r_t = \sum_{i=1}^{\infty} \alpha_i r_{t-i} + \sum_{i=0}^{\infty} \beta_i x_{t-i} + \varepsilon_{rt}, \]

(3)

\[ x_t = \sum_{i=1}^{\infty} \delta_i r_{t-i} + \sum_{i=1}^{\infty} \eta_i x_{t-i} + \varepsilon_{xt}. \]

In model (3), the first equation formulates the trade-by-trade evolution of the bid-ask midpoint; the second one indicates the persistence of the order flow. The \( x_{jt} \) is an indicator variable for stock \( j \) in trade \( t \) (+1 for buying; -1 for selling), and \( r_{jt} \) is the log return based on the bid-ask midpoint for stock \( j \) in trade \( t \), while \( \text{var}(\varepsilon_{rt}) = \sigma_r^2 \), \( \text{var}(\varepsilon_{xt}) = \sigma_x^2 \) are assumed to be held6. Using tick-by-tick data, we estimate these two equations by taking ordinary least squares (OLS) for each day and each stock.

5 Following Hasbrouck (1991b), the lagging 3 periods are employed.

6 The stock subscript \( j \) is omitted from now on.
Under some assumptions, the vector auto-regression (VAR) form of equation (3) can be inverted into a vector moving average (VMA) representation

\[ y_t = [r_t \ x_t] = [a(L) \ b(L) \ d(L) \ e(L)] \begin{bmatrix} \varepsilon_{rt} \\ \varepsilon_{xt} \end{bmatrix}. \] \hspace{1cm} (4)

Following Hasbrouck (1991b), \( a(L), b(L), d(L), \) and \( e(L) \) are the lag polynomial operators. The sum of \( a(L) \varepsilon_{rt} + b(L) \varepsilon_{xt} \) is the permanent impact of an innovation on the price. Assuming \( \text{cov}(\varepsilon_{rt}, \varepsilon_{xt}) = 0 \), the variance of the random-walk component can be written as follows:

\[ \sigma^2 = (\sum_{i=0}^{\infty} a_i)^2 \sigma^2_r + (\sum_{i=0}^{\infty} b_i)^2 \sigma^2_x. \] \hspace{1cm} (5)

As in Hasbrouck (1991b), the first term of equation (5) measures the component of the price discovery that is unrelated to trading, and the second term captures the part of the price discovery that is related to the recent trade. The sum of the first term and the second term is called the price discovery or the efficient price change.

(3) Robust test for price discovery

To better understand the differences in the price discovery and its two components before and after the transparency event, we follow the methodology used by Hendershott et al. (2011) and Riordan and Storkenmaier (2012) and run a regression with controlled variables. The fixed effects are also considered, and, essentially, this becomes a robustness test. The controlled variables include: stock price, which is the natural log of the average trading price for stock \( i \) on day \( t \); shares, which is the natural log of the trading shares for stock \( i \) on day \( t \); and market value, which is the natural log of market value for stock \( i \) on day \( t \). The regression model is

\[ L_{i,t} = \alpha_i + \beta_1 \text{Dummy}_{i,t} + \sum_{k=1}^{3} \psi_k \text{Controls}_{i,t,k} + \varepsilon_{i,t}, \] \hspace{1cm} (6)

where \( L_{i,t} \) is the cumulative impulse response, trade-related standard deviation, quote-related standard deviation, and price discovery for stock \( i \) on day \( t \); \( \text{Dummy}_{i,t} \) is a dummy variable, with a value of 0 if before the event and 1 otherwise; \( \varepsilon_{i,t} \) is an error term, assuming it follows classical rules; and \( \text{Controls}_{i,t,k} \) are the control factors.

(4) The interaction between the changes in efficiency and price discovery

We follow the methodology of Amihuld et al. (1997) and Muscarella and Piwowar (2001) to test the interaction between changes in price efficiency and price discovery attributed to a greater transparency impact. The cross-sectional regression models are as follows:

\[ d\text{priced}_y_i = \alpha_i + \beta_1 \beta_i \cdot d1 + \beta_i + \kappa_i, \] \hspace{1cm} (7)
\[ d\text{priced}y_i = \alpha_i + \beta_1 \sigma_i \epsilon_i + \kappa_i, \] 

where, for stock \( i \), \( d\text{priced}y_i \) is the price discovery change; \( d1\beta_i \) is the change of lag response; and \( d\text{Var}(\epsilon_i) \) is the firm-specific noise change, respectively.

6. Empirical findings

This section describes the basic statistics of our sample and the empirical findings obtained in this study.

6.1. Descriptive statistics

Table 1 contains descriptive statistics for the sample of all firms, both large and small. The characteristics of the average daily closing price, average daily volatility, average daily trading shares, and average daily market value are reported. Examining the stocks in each portfolio, we find that large firms have bigger values than small firms in all fields. For example, the average trading shares for large firms are 12,502, while they are 849 for small firms. According to TSEC statistics, institutional investors prefer large firm stocks over small firm stocks and, as a result, the trading of large firms is more intensive than the trading of small firms.

Table 1 Descriptive statistics from the Taiwan Stock Exchange

This table reports the mean values of daily closing price, volatility (the highest price minus the lowest price each day), daily traded shares (in thousands), and daily market value (in millions) for all stocks and for two sub-sample stocks. We sorted the firms listed on the TSEC based on their 2001 year-end capitalization and divided them equally into three groups. The first group (large firms) includes stocks with the largest capitalization, and the third one (small firms) is composed of stocks with the smallest capitalization. Numbers reported below are during the period Sept. 1, 2002, to April 30, 2003.

<table>
<thead>
<tr>
<th>Market value portfolio</th>
<th>All firms</th>
<th>Large firms</th>
<th>Small firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>28.54</td>
<td>37.08</td>
<td>20.00</td>
</tr>
<tr>
<td>Volatility</td>
<td>1.01</td>
<td>1.32</td>
<td>0.70</td>
</tr>
<tr>
<td>Trading shares (in thousands)</td>
<td>6676</td>
<td>12502</td>
<td>849</td>
</tr>
<tr>
<td>Market value (in millions)</td>
<td>31033</td>
<td>60242</td>
<td>1824</td>
</tr>
<tr>
<td>Number of stocks</td>
<td>200</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>
6.2. Improvements in efficiency

In this section, we compare the three measurements of RRD, lag response, and firm-specific noise before and after the transparency event to infer the improvement in efficiency.

The behavior of $RRD_s$ is shown in Fig. 1 - Fig. 3. From the patterns shown in these figures, it is found that the market becomes more efficient after the transparency event, impacting both large and small firms. For example, for total (large, small) firms, the average $RRD_s$ is 3.71 (3.65, 3.77) during the pre-event period, while the value decreases to 2.92 (2.72, 3.13) in the post-event period-- a difference of -0.79 (-0.93, -0.64); the corresponding T value is -6.82 (-5.43, -4.23). At the same time, $RRD_s$ begins to decrease, becoming more concentrated about 30 days after the event day for total firms, large firms, and small firms. This phenomenon suggests that investors adjust their behaviors gradually, not immediately, to changes in market condition.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{RRD.png}
\caption{Relative Return Dispersion (Total firms)}
\end{figure}

This figure reports the Relative Return Dispersion (RRD) before and after the event. The period before the event ranges from September 1, 2001, to December 31, 2002; the period after the event ranges from January 2, 2003, to April 30, 2003. There are 100 large firms and 100 small firms in our sample. The RRD for day $t$ is defined by

$$RRD_t = \frac{1}{N} \sum_{i=1}^{N} \varepsilon_{it}^2.$$  Here $\varepsilon_{it}$ is the market model residual of stock $i$ on day $t$. The market model is estimated separately for the pre-event period ($t=-85$ to $t=-1$) and post-event period ($t=0$ through $t=75$),
and N is the number of stocks. The two horizon lines are the means for RRD before and after the event.

**Figure 2** Relative Return Dispersion (Large firms)
This figure reports the Relative Return Dispersion (RRD) before and after the event. The period before the event ranges from September 1, 2001, to December 31, 2002; the period after the event ranges from January 2, 2003, to April 30, 2003. There are 100 large firms and 100 small firms in our sample. The RRD for day t is defined by

\[
RRD_t = \frac{1}{N} \sum_{i=1}^{N} \epsilon_{it}^2.
\]

Here \( \epsilon_{it} \) is the market model residual of stock i on day t. The market model is estimated separately for the pre-event period (t=-85 to t=-1) and post-event period (t=0 through t=75), and N is the number of stocks. The two horizon lines are the means for RRD before and after the event.

**Figure 3** Relative Return Dispersion (Small firms)
This figure reports the Relative Return Dispersion (RRD) before and after the event. The period before the event ranges from September 1, 2001, to December 31, 2002; the period after the event ranges from January 2, 2003, to April 30, 2003. There are 100 large firms and 100 small firms in our sample. The RRD for day t is defined by

\[
RRD_t = \frac{1}{N} \sum_{i=1}^{N} \epsilon_{it}^2.
\]

Here \( \epsilon_{it} \) is the market model residual of stock i on day t. The market model is estimated separately for the pre-event period (t=-85 to t=-1) and post-event period (t=0 through t=75), and N is the number of stocks. The two horizon lines are the means for RRD before and after the event.
and \( N \) is the number of stocks. The two horizon lines are the means for RRD before and after the event.

We next examine two other factors: the lag response and the firm-specific noise. The results are shown in Table 2. It can be seen that there is a significant decrease in both the lag response and firm-specific noise after the transparency event. For example, the lag response of large (small) firms decreased from 0.046 (0.095) to -0.015 (0.035), and the firm-specific noise decreased from 5.456 (5.765) to 4.325 (5.013). The decrease in lag response means that investors are adjusting their behaviors to market information faster than before, inducing stock prices to promptly react to new information. The decrease of firm-specific noise after the event implies either a reduction in price error or that more firm-specific information is incorporated into the stock price more precisely. Overall, hypothesis H1 is rejected as the market becomes more efficient following the opening of limit-order books.

**Table 2 Efficiency change around the event**

The market model: \( R_{it} = \alpha_i + \beta_i R_{M_t} + 1\beta_i R_{M_{t-1}} + \epsilon_{it} \) is estimated using the OLS firm by firm before and after the transparency event. Here, \( R_{it} \) is the daily return on stock \( i \) on day \( t \); \( R_{M_t} \) is the market return on day \( t \); \( \epsilon_{it} \) is the residual term; and \( \alpha_i \) is the intercept term. The \( \beta_i \) and \( 1\beta_i \) are the coefficients of current market return and lag market return, respectively. The pre-event period is from September 1, 2001, to December 31, 2002. The post-event period is from January 2, 2003, to April 30, 2003. There are 100 large firms and 100 small firms in our sample. The means of the estimated coefficient \( 1\beta \) and the variance of residual term are calculated across all firms. Differences that are significantly different from 0 are denoted by *, **, and *** at the 10%, 5%, and 1% significance levels, respectively.

<table>
<thead>
<tr>
<th>Measures of efficiency</th>
<th>Lag response (1( \beta ))</th>
<th>Firm-specific noise (var(( \epsilon )))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean-before event</td>
<td>0.071</td>
<td>5.610</td>
</tr>
<tr>
<td>Mean-after event</td>
<td>0.010</td>
<td>4.669</td>
</tr>
<tr>
<td>Diff. (t-value)</td>
<td>-0.061</td>
<td>-0.941</td>
</tr>
<tr>
<td></td>
<td>(-4.25***)</td>
<td>(-5.12***)</td>
</tr>
<tr>
<td><strong>Large firms</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean-before event</td>
<td>0.046</td>
<td>5.456</td>
</tr>
<tr>
<td>Mean-after event</td>
<td>-0.015</td>
<td>4.325</td>
</tr>
<tr>
<td>Diff. (t-value)</td>
<td>-0.061</td>
<td>-1.131</td>
</tr>
<tr>
<td></td>
<td>(-3.05***)</td>
<td>(-4.82**)</td>
</tr>
<tr>
<td><strong>Small firms</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean-before event</td>
<td>0.095</td>
<td>5.765</td>
</tr>
<tr>
<td>Mean-after event</td>
<td>0.035</td>
<td>5.013</td>
</tr>
</tbody>
</table>

15
Diff. & -0.060 & -0.752 & \\
(t-value) & (-2.96*** & (-2.68*** & \\

6.3 Changes in price discovery around the event

Hypotheses H2a-H2c, namely disclosure of limit-order books, has no effect on the components of price discovery, and the price discovery itself will be tested. The descriptive statistics are examined first. The first column in Table 3 shows the cumulative impulse response, which is viewed as the permanent price impact of a trade and is usually interpreted as indicating the private information content of a trade. Although the cumulative impulse response is shown to decrease post event for firms overall, it increases for large firms and decreases for small firms. There are two components to price discovery: trade-related standard deviation and quote-related standard deviation. The former relates to private information while the latter connects to public information. Table 3 shows that the trade-related standard deviation increases post-event, while the quote-related standard deviation decreases for firms overall, but the impact is different for differently sized firms. Price discovery itself increases for firms overall, decreases for large firms, and increases for small firms after the event.
Table 3 Descriptive statistics for price discovery

This table reports the cumulative impulse response, trade-related standard deviation, quote-related standard deviation, and the sum of both for the pre-event and post-event period. The period before the event ranges from September 1, 2001, to December 31, 2002. The post-event period ranges from January 2, 2003, to April 30, 2003. The numbers in the table are the means before and after the event, respectively. The unit is the basis point. There are 100 large firms and 100 small firms in our sample.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Cumulative impulse response (1)</th>
<th>Trade-related standard deviation (2)</th>
<th>Quote-related standard deviation (3)</th>
<th>Price discovery (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Overall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before event</td>
<td>16.09</td>
<td>7.79</td>
<td>60.89</td>
<td>68.68</td>
</tr>
<tr>
<td>After event</td>
<td>15.71</td>
<td>12.45</td>
<td>59.25</td>
<td>71.70</td>
</tr>
<tr>
<td>Diff.</td>
<td>-0.48</td>
<td>4.66</td>
<td>-1.46</td>
<td>3.02</td>
</tr>
<tr>
<td><strong>Panel B: Large firms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before event</td>
<td>3.86</td>
<td>3.30</td>
<td>77.28</td>
<td>80.58</td>
</tr>
<tr>
<td>After event</td>
<td>5.73</td>
<td>4.97</td>
<td>64.99</td>
<td>69.96</td>
</tr>
<tr>
<td>Diff.</td>
<td>1.87</td>
<td>1.67</td>
<td>-12.29</td>
<td>-10.62</td>
</tr>
<tr>
<td><strong>Panel C: Small firms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before event</td>
<td>32.51</td>
<td>13.82</td>
<td>38.89</td>
<td>52.71</td>
</tr>
<tr>
<td>After event</td>
<td>31.20</td>
<td>24.07</td>
<td>50.34</td>
<td>74.40</td>
</tr>
<tr>
<td>Diff.</td>
<td>-1.31</td>
<td>10.25</td>
<td>11.45</td>
<td>21.69</td>
</tr>
</tbody>
</table>

The above results are purely descriptive. The panel data method is used to test the differences in the cumulative impulse response, trade-related standard deviation, quote-related standard deviation, and price discovery pre- and post- the event, including consideration of controlled variables with firm fixed effects, as in model (6). The regression results are shown in Table 4. First, for firms overall, the differences in all four measures are not significant. Further, large firms and small firms are separately observed. There is a significant increase in the cumulative impulse response and the trade-related standard deviation for large firms after the event, while the quote-related standard deviation decreases. They offset each other, leading to no unobvious alteration in price discovery. The results imply that, although there is no significant change in price discovery post-event, the trade reveals more private information than was the case pre-event. In other words, greater transparency moves the market toward strong form efficiency for large firms. For small firms post-
event, there is a significant increase in quote-related standard deviation and the price discovery, while the other measures do not change significantly. The increase in quote-related deviation means that a trade reveals more public information to the market than pre-event, making the market semi-strong in terms of efficiency for small firms. The increase in price discovery measures indicates that the impact of transparency is beneficial to price discovery for small firms. However, from the above results, it is very complicated to make conclusions about H2a-H2c. From a bird’s-eye view, we can say the transparency event affects the components of price discovery or price discovery itself, but the impacts are different for differently sized firms. The outcomes are also consistent with the positive argument of O’Hara (1995) on transparency issues.
Table 4 Regression for price discovery with fixed effects

This table reports the regression results for cumulative impulse response, trade-related standard deviation, quote-related standard deviation, and efficient price change (price discovery), which is the sum of the trade-related and quote-related standard deviation. The period before the event ranges from September 1, 2001, to December 31, 2002; the period after the event ranges from January 2, 2003, to April 30, 2003. There are 100 large firms and 100 small firms in our sample. The model is formulated as follows: \( S_{dSDv_i,t} = \alpha_i + \beta_{i1} C(p)_t + \beta_{i2} \ln(shes)_t + \beta_{i3} \ln(mv)_t + \gamma_i D_{LT} + \epsilon_{LT} \), where \( S_{dSDv_i,t} \) is the cumulative impulse response, trade-related standard deviation, quote-related standard deviation, and efficient price change (price discovery) of stock \( i \) at time \( t \); \( ln(p)_t \), the \( p \) is the average trading price for stock \( i \) at time \( t \); \( ln(shes)_i,t \), were \( shes \) is the average trading shares (in thousands) for stock \( i \) at time \( t \); \( ln(mv)_i,t \), where \( mv \) is the market value of stock \( i \) at time \( t \); \( D_{LT} \) is a dummy variable, and its value is 0 if before the event or 1 otherwise; \( \epsilon_{LT} \) is an error term. We take the natural log of these controlled variables. The model is regressed on a daily measure, and the fixed effect is also considered. For simplicity, only dummy variable and corresponding t-values are displayed. The symbols ** and *** denote statistical significance at the 5% and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Cumulative impulse response (1)</th>
<th>Trade-related standard deviation (2)</th>
<th>Quote-related standard deviation (3)</th>
<th>Price discovery (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Overall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy estimate</td>
<td>-4.70</td>
<td>3.99</td>
<td>2.68</td>
<td>6.67</td>
</tr>
<tr>
<td>t-value</td>
<td>-0.59</td>
<td>1.33</td>
<td>1.01</td>
<td>1.54</td>
</tr>
<tr>
<td><strong>Panel B: Large firms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy estimate</td>
<td>2.17</td>
<td>1.99</td>
<td>-4.70</td>
<td>-2.70</td>
</tr>
<tr>
<td>t-value</td>
<td>2.99***</td>
<td>3.32***</td>
<td>-1.88</td>
<td>-1.00</td>
</tr>
<tr>
<td><strong>Panel C: Small firms</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy estimate</td>
<td>-10.50</td>
<td>8.65</td>
<td>15.05</td>
<td>23.70</td>
</tr>
<tr>
<td>t-value</td>
<td>-0.54</td>
<td>1.20</td>
<td>2.80***</td>
<td>2.45**</td>
</tr>
</tbody>
</table>

**estimates are basis point

6.4 The interaction between efficiency and price discovery

Finally, we test whether the improvements in efficiency and price discovery, which were brought about by a transparency impact, are correlated. Essentially, we follow the methodology developed by Amihuld et al. (1997) and Muscarella and Piwowar (2001). The models to be tested are model (7) and model (8), and the results are shown in Table 5. As shown, none of the T values have significance above the 5% significance level, and H3 is not rejected. The results imply that there is no interaction
between changes in efficiency and price discovery, that is, improvement in efficiency
does not go any further to stimulate price discovery.

Table 5 Interaction between price discovery and efficiency

This table reports the estimates of the cross-sectional regression models: 
\[ dpred_{dt} = \alpha_i + \beta_1 d1 \beta_i + \kappa_i \] 
and \[ dpred_{dt} = \alpha_i + \beta_2 Var(\varepsilon)_i + \kappa_i \], formulated to examine the interaction between changes in 
price discovery and efficiency due to the transparency event. The symbol \( dpred \) means the change 
of price discovery; \( 1 \beta_i \) and \( Var(\varepsilon)_i \) come from the simple market mode: 
\[ R_i = \alpha_i + \beta_i R_{i-1} + \varepsilon_{i1} \] 
and \( d \) means change before and after the transparency event. The numbers in the table are the 
estimated coefficients and the corresponding t values.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Changes in price discovery (( dpred ))</th>
<th>Corresponding T value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent variable</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change of lag response ( (1 \beta) )</td>
<td>-4.21</td>
<td>-0.62</td>
</tr>
<tr>
<td>Firm-specific noise change ( (Var(\varepsilon)) )</td>
<td>0.41</td>
<td>0.72</td>
</tr>
<tr>
<td><strong>Large firms</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change of lag response ( (1 \beta) )</td>
<td>2.92</td>
<td>0.54</td>
</tr>
<tr>
<td>Firm-specific noise change ( (Var(\varepsilon)) )</td>
<td>0.26</td>
<td>0.53</td>
</tr>
<tr>
<td><strong>Small firms</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change of lag response ( (1 \beta) )</td>
<td>-13.26</td>
<td>-0.97</td>
</tr>
<tr>
<td>Firm-specific noise change ( (Var(\varepsilon)) )</td>
<td>0.38</td>
<td>0.38</td>
</tr>
</tbody>
</table>

All estimates are multiplied by \( 10^3 \).

7. Conclusion

Transparency is a topic of importance to all participants in the stock market. Most
previous research has focused on examining pre-trade transparency, while this study empirically investigates the change that occurs post-trade transparency and the increased opening of limit-order books after each trade. This study focuses on three different but related issues: efficiency, price discovery, and the interaction of the changes in both.

Several findings emerge from this analysis. Consistent with the assumption of regulators and policy makers, greater transparency upgrades market efficiency for both large and small firms and implies that investors impound information into stock prices faster than before. For price discovery, under greater transparency, a trade impacts the stock prices of large firms more than that of small firms. Additionally, that trade reveals more private information for the large firms, whereas for the small firms, it generally conveys more public information. The outcomes indicate that the increased transparency shifts the large firm stocks closer to a strong form efficient market but a semi-strong form efficient market for small firms. Finally, no interaction between efficiency and price discovery can be found, implying the improvement in efficiency does not accelerate price discovery.

This study’s findings are consistent with the theoretical argument that traders adjust their trading behavior depending on the level of transparency. This affects market efficiency, the components of price discovery, or price discovery itself. All in all, the findings support the view that greater transparency has a positive impact on market quality.
References


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