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## Finance Research Letters

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# Technology upgrades in emerging equity markets: Effects on liquidity and trading activity<sup>☆</sup>

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## ARTICLE INFO

*Article history:*

Received 20 January 2015

Accepted 9 May 2015

Available online xxxx

*JEL classification:*

G12

G14

G15

G23

*Keywords:*

Market microstructure

Technological upgrade

High frequency trading

Emerging markets

Liquidity

## ABSTRACT

This study examines the effects of technological changes on liquidity of stock markets. Utilizing daily data of 361 stocks from 10 emerging market exchanges, namely Colombia, Indonesia, Johannesburg, Korea, Malaysia, Mexico, Russia, Shanghai, Shenzhen and Thailand, a panel data regression analysis shows that technological upgrade decreases the bid-ask spread and increases trading activity. In other words, launching a more sophisticated trading platform contributes to the overall liquidity of the market.

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## 1. Introduction

For many years, developments in technology have been a core topic on the agenda of the exchange industry. Since technological upgrades modernize the way financial assets are traded, investments in exchange infrastructures improve the strength of the link between investment and savers. With the inclusion of technology in trading activities, the cost incurred by intermediaries decreases, thereby not only enabling more efficient risk sharing, but also improving hedging strategies, liquidity, and efficiency of prices (Hendershott et al., 2011).

<sup>☆</sup> The views expressed in this work are those of the authors and do not necessarily reflect those of Borsa İstanbul or its members.

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<http://dx.doi.org/10.1016/j.frl.2015.05.012>

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Following the advance of electronic platforms, institutional investors have switched their focus to fully electronic trading systems, namely algorithmic trading. Algorithmic trading may be defined as the use of computer programmes to enter trading orders where the computer algorithm decides on aspects of execution of the order such as the timing, quantity and price of the order (European Commission, 2010). Currently the most popular type of algorithmic trading is high-frequency trading (HFT) where a large number of orders are sent into the market at high speed, with round-trip execution times measured in microseconds (Brogaard, 2010). Such a trading environment makes the speed and quality of access to the market a crucial component of the competition between the exchanges.

In this paper we investigate the effects of technological changes on bid-ask spreads and trading activity. What is meant by technological change here is an upgrade in trading systems and/or launch of a new trading platform which significantly decreases latency. Changes which do not significantly contribute to reducing latency are not considered as technological upgrades.

While previous studies primarily focus on liquidity and volatility, we particularly give attention to trading activity metrics. The reason for doing so is that, different from advanced markets, emerging stock exchanges expect significant improvements not only in market quality, but also in overall level of trading activity. To the best of our knowledge, we provide one of the first studies in this particular field of research focused on emerging markets. By utilizing stock-level daily data from ten stock exchanges, we determine that liquidity and trading activity are positively affected by technology upgrades. Having controlled for global trends and stock-related variables, our results were found to be robust with different dates of upgrades further strengthening our results.

## 2. Literature

Using either date of introduction of new technologies or volume of algorithmic/HF trading as a proxy for technological development, number of studies reveal the relationship between several variables -mainly liquidity, efficiency and volatility- and technological changes.

Focusing on the introduction of new technologies is also useful when the reverse side is considered. If algorithmic and/or HFT<sup>1</sup> finds itself as the main concern, using the introduction of new technologies as an instrumental variable reflecting the algorithmic trading/HFT activity solves the endogeneity problem which arises from the fact that such trading activity is also affected by market variables (Hendershott et al., 2011; Boehmer et al., 2014). Difficulty in tracking the algorithmic trading and HFT data is, of course, another reason behind the decision to use such a variable.

There are a number of studies focusing on spreads as liquidity measure. Hendershott and Moulton (2011) document that, by reducing the execution time for market orders from 10 s to less than one second, not only does the cost of immediacy (bid-ask spread) increase due to increased adverse selection, but so is the noise in prices reduced, thereby making prices more efficient. Hendershott et al. (2011), utilizing daily average data, report that for large stocks in particular, algorithmic trading narrows spreads, reduces adverse selection, and reduces trade-related price discovery, which then improves liquidity and enhances the informativeness of quotes. Hasbrouck and Saar (2013) report that rise in the volume of low-latency trades lowers spreads while also increasing the depth of the limit order book.

Riordan and Storkenmaier (2012) provide similar evidence from Europe. They examine the upgrade of the Deutsche Börse trading system with the release of Xetra 8.0., and show that decreasing latency leads to increased liquidity by decreasing bid-ask spreads while also improving the efficiency of prices.

<sup>1</sup> To clarify the descriptions, it is worth noting that high-frequency trading (HFT) is a subset of algorithmic trading, which refers to all trading activity performed through computer algorithms. As Hasbrouck and Saar (2013) suggests, the more structural difference lies in the nature of trading: "We can categorize algorithmic activity as proprietary or agency. We consider HFT a subcategory of proprietary algorithms for which low latency is essential. . . Agency algorithms are used by buy-side institutions . . . to minimize the cost of executing trades in the process of implementing changes in their investment portfolios. . . Such proprietary algorithms try to make profit from the trading environment itself (as opposed to investing in stocks), employed by hedge funds, proprietary trading desks of large financial firms, and independent specialty firms."

**Table 1**

Technology upgrades. Source: WFE Focus monthly newsletter and Exchanges' releases. The texts of the announcements are available from authors upon request. Speed, capacity and functionality are common themes across the upgrades.

Exchange	Date of upgrade	Technology provider
Bursa Malaysia	01.12.2008	NYSE
Shenzhen SE	12.01.2009	STS (in-house)
Colombian SE	09.02.2009	NASDAQ X-Stream
Indonesia SE	09.03.2009	JATS-NEXT (by NASDAQ)
Korea Exchange	23.03.2009	EXTURE (in-house)
Shanghai SE	04.12.2009	NGTS (in-house)
Johannesburg SE	02.07.2012	Millenium IT
Mexican SE	03.09.2012	MoNet (in-house)
Thailand SE	03.09.2012	SET CONNECT (in-house)
Moscow Exchange	08.12.2012	Spectra

On the other hand, [Gai et al. \(2012\)](#) find that an increase in speed does not decrease the bid-ask spread. They find that although an increase in trading speed also increases message flow, the rise in message flow is due to an increase in order cancellations without any real increase in actual trading volume. [Boehmer et al. \(2014\)](#) find that more intense algorithmic trading is associated with improved liquidity, improved efficiency and increased volatility. Similarly, [Easley et al. \(2014\)](#) report that a major upgrade in NYSE generated a relatively greater turnover and relatively lower transaction costs.

There are two studies focusing on a single emerging country. [Krishnamurti et al. \(2003\)](#) argue that level of technology in India's two exchanges (NSE and BSE) positively affects the attention of small and medium investors. [Dicle and Levendis \(2013\)](#) study the effect of a technological upgrade on the Johannesburg SE in 2002. Utilizing daily data for ten years, they find that while liquidity improves following the upgrade, the level of efficiency remains unchanged.<sup>2</sup>

### 3. Data

We explore the technological upgrades in equity markets of exchanges in emerging countries searching from the beginning of 2005. If we are able to obtain the initial implementation date of the new technology, we add that market to our sample. Our final sample consists of 10 exchanges ([Table 1](#)).

The geographical dispersion of the sampled exchanges is thought to have a high level of representative power: There are two exchanges from the Americas, six exchanges from the Asia-Pacific, and one exchange from Africa and Eastern Europe, each. The sample is also diversified in terms of level of development and fields of specialization.

Our study exploits daily stock market data. We conduct a panel data analysis by using daily data of 361 stocks from the exchanges listed above. Stocks included in the blue-chip indices are included. If a blue-chip index contains more than 50 stocks – which is the case for two of ten exchanges – we sort the stocks according to their weights on the index and select the first 50 of them. Source of the data is Bloomberg. The variables obtained are closing/highest/lowest price, return, traded value, trading volume, bid-ask spread, market capitalization and market-to-book ratio. Each of the series includes the daily closing values of the variables for both three years before and after the upgrade. If the post-upgrade period is less than 3 years for an exchange, we adjust the estimation windows accordingly, keeping the length of pre- and post-upgrade periods the same. The daily closing values of the CBOE Volatility Index (VIX<sup>3</sup>) and MSCI Emerging Index (MXEF) are also included.

<sup>2</sup> Our study also touches on another strand of literature which deals with a broader scope and which gives more attention to the volume of trading activity and cost of equity. [Jain \(2005\)](#), [De la Torre et al. \(2007\)](#), and [Lagoarde-Segot \(2009\)](#) are among those examining the country-level factors affecting the equity trading activity. Such studies utilize data aggregated at the exchange level (monthly in general) and search for the effects of several institutional factors. These cross-country studies mostly document the effects of introducing electronic trading into stock exchanges.

<sup>3</sup> Chicago Board Options Exchange Volatility Index, measure of implied volatility of S&P 500 index options. It is a representation of one measure of the market's expectations of stock market volatility over the next 30 day period. It is sometimes referred as fear index.

#### 4. Methodology

To explore the nature of change in the market following the technological upgrade, we focus on the effect of technological upgrades on spreads and volume of trading activity. First, following Hendershott et al. (2011), in order to test the effect of technology on stock liquidity, we adopt the following panel regression model:

$$\mathcal{L}_{it} = \alpha_i + \gamma_t + \beta T_{it} + \delta X_{it} + \varepsilon_{it} \quad (1)$$

where  $\mathcal{L}_{it}$  denotes the liquidity of stock  $i$  at day  $t$ .  $T_{it}$  is the dummy variable taking the value of 0 before the technology upgrade implementation date, and 1 afterward.  $X$  consists of the matrix of control variables, including price change of the stock on day  $t$  ( $P_{it} - P_{it-1}$ ); daily volatility, calculated as  $((P_{it})_{high} - (P_{it})_{low}) / ((P_{it})_{high} + (P_{it})_{low}) / 2$ ; and the daily close value of the VIX. The reason we choose VIX as a control variable is that it is known to be an appropriate indicator for global stress and reflects the volatility effect coming from outside of the market. While firm fixed effects are included in  $\alpha_i$ , day fixed effects are included in  $\gamma_t$ . All series are checked for stationarity.

We use relative quoted spread as the proxy for liquidity. For a given day  $t$  and stock  $i$ , the relative quoted spread, standardized by the quote midpoint, may be defined as:

$$RQS_{it} = (Ask_{it} - Bid_{it}) / \left( \frac{Ask_{it} + Bid_{it}}{2} \right) \quad (2)$$

where  $Ask_{it}$  refers to the minimum price that sellers are willing to receive for stock  $i$  at time  $t$ ,  $Bid_{it}$  refers to the maximum price that buyers are willing to pay for stock  $i$  at time  $t$ . We expect the coefficient of  $T$ ,  $\beta$ , to be negative in Eq. (1).

Second, we include three different measures to gauge trading activity: trading volume, traded value and turnover. Trading volume is the total number of stocks traded. Traded value is the total number of shares traded multiplied by their respective matching prices. Turnover is the ratio of traded value to the market capitalization. We adopt the following panel data regression model, which we repeat for three trading activity measures:

$$\log(V_{it}) = \alpha_i + \gamma_t + \beta T_{it} + \delta Y_{it} + \varepsilon_{it} \quad (3)$$

where  $V_{it}$  denotes the trading activity of stock  $i$  at day  $t$  and  $T_{it}$  is the same as in Eq. (1).  $Y$  represents the matrix of control variables, including lagged returns of the stock for up to five days, the daily closing values of the VIX, and the market-to-book ratio.

For each of the dependent variables described above, we conduct both an overall and exchange-based panel data analyses. We first combine all of exchanges' data sets into a single data set and make analyses. Second, we repeat the tests for each of the exchanges separately.

#### 5. Results

As shown in Table 2, we find that while the upgrades have a positive effect on trading activity measures in agreement with Easley et al.'s (2014) findings, they have a negative effect on spreads. Our findings on spreads are in line with Riordan and Storkenmaier (2012) and Boehmer et al. (2014), whereas they contradict Hendershott and Moulton's (2011) results. Riordan and Storkenmaier (2012) explain the reason behind their results differing with those of Hendershott and Moulton (2011) by pointing out that their study (2012) contains a microstructure change which may unintentionally encompass other effective factors, such as an increase in anonymous trading. We may argue that, as our sample consists of emerging markets, marginal effect of improvements in technical capacity on liquidity may be more significant with respect to the advanced markets.

When we look at the stock-level results across the exchanges, our results show that spreads narrowed in 6 of the 9 exchanges<sup>4</sup> (Panel A of Table 3), the spreads widened in 2 exchanges, and remained unchanged in 1 exchange. The spreads widened in Johannesburg Stock Exchange and Moscow Exchange though the value of coefficients are very low while did not change in Shanghai Stock Exchange. Among the exchanges where the spreads narrowed, Indonesian and Korea exchanges have the largest coefficients of the technology change.

Regarding trading activity, we find that although traded value increased in all of the sampled exchanges, trading volume and turnover increased in 9 and 7 out of the 10 exchanges, respectively (Panel B of Table 3). Trading volume did not change in Colombian Stock Exchange. Turnover did not change in Colombian Stock Exchange, Bursa Malaysia, and Moscow

<sup>4</sup> We were not able to find the spread data for the Colombian exchange.

**Table 2**  
Results of the pooled panel regressions.

Dependent variable	Effect of technological change
Relative quoted spread (Eq. (1))	−0.0027 <sup>***</sup>
Traded value (Eq. (3))	3.0002 <sup>***</sup>
Trading volume (Eq. (3))	1.9349 <sup>***</sup>
Turnover (Eq. (3))	0.9519 <sup>***</sup>

Coefficients of the control variables are available from authors upon request.  
\*\*\* Statistical significance at the 1% level.

**Table 3**  
Results of the panel regression for technology upgrades across exchanges.

Exchange	Effect of technological change
<i>Panel A: Dependent variable: relative quoted spread (Eq. (2))</i>	
Indonesian SE	(−0.0058) <sup>***</sup>
Johannesburg SE	0.0001 <sup>**</sup>
Colombian SE	–
Korea Exchange	(−0.0054) <sup>***</sup>
Bursa Malaysia	(−0.0027) <sup>***</sup>
Mexican Exchange	(−0.0015) <sup>***</sup>
Moscow Exchange	0.0002 <sup>**</sup>
Shanghai SE	(−1.8) × 10 <sup>−6</sup>
Shenzhen SE	(−0.0007) <sup>***</sup>
Thailand SE	(−0.0002) <sup>***</sup>
Pooled	(−0.0027) <sup>***</sup>

Exchange	Effect of technological change		
	(Dep. Var: Traded value)	(Dep. Var: Trading volume)	(Dep. Var: Turnover)
<i>Panel B: Dependent variables: trading volume, traded value, and turnover (Eq. (3))</i>			
Indonesian SE	2.5534 <sup>***</sup>	1.5131 <sup>***</sup>	0.7690 <sup>***</sup>
Johannesburg	3.2364 <sup>***</sup>	0.0723 <sup>***</sup>	1.5943 <sup>***</sup>
Colombian SE	0.5163 <sup>***</sup>	0.0615	−0.0051
Korea Exchange	2.7622 <sup>***</sup>	1.2379 <sup>***</sup>	0.7722 <sup>***</sup>
Bursa Malaysia	0.6936 <sup>***</sup>	0.3881 <sup>***</sup>	0.0350
Mexican Exchange	2.8385 <sup>***</sup>	0.2847 <sup>***</sup>	0.2575 <sup>***</sup>
Moscow Exchange	2.7796 <sup>***</sup>	2.1370 <sup>***</sup>	0.0001
Shanghai SE	3.9460 <sup>***</sup>	3.2862 <sup>***</sup>	1.3729 <sup>***</sup>
Shenzhen SE	3.5756 <sup>***</sup>	2.7381 <sup>***</sup>	1.4553 <sup>***</sup>
Thailand SE	4.3712 <sup>***</sup>	3.3368 <sup>***</sup>	0.1128 <sup>***</sup>
Pooled	3.0002 <sup>***</sup>	1.9349 <sup>***</sup>	0.9519 <sup>***</sup>

Coefficients of the control variables are available from authors upon request.

\*\* Statistical significance at the 5% level.

\*\*\* Statistical significance at the 1% level.

Exchange. Thailand Stock Exchange has the highest increase in traded value and trading volume whereas Johannesburg Stock Exchange has the highest increase in turnover. The two Chinese exchanges ranked second and third in all of three trading activity measures.

## 6. Conclusion

Utilizing daily data series of 10 exchanges, we explore the effects of technological upgrades on market structures. These upgrades are expected to be game changers for these exchanges,

reflecting their strategy of reaching higher levels of trading volumes together with more efficient markets.

Our study is one of the first studies focusing on emerging markets and gives new evidence for the ongoing debates. We find that spreads narrow and trading activity increases following the upgrades. Our findings on spreads confirm, for the most part, previous studies' findings. All the results support that technological capacity is worth investment regarding the business environment of the exchange industry shaped by competitive pressures exerted by other exchanges and new trading schemes such as algorithmic trading and HFT.

For the emerging markets, it seems that the effects of technological changes will remain prominent in the near future. Hence, the different characteristics of these changes as well as how they are compared with advanced markets may be valuable questions for future research.

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