J-REIT Market Quality: Impact of High Frequency Trading and the Financial Crisis

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Abstract

Using the introduction of Arrowhead low latency trading platform by Tokyo Stock Exchange as a natural experiment, I analyze the impact of high frequency trading on market quality of J-REITs, in terms of liquidity, volatility, and systemic risks. I also analyze the impact of the 2008 financial crisis. The results document that while the crisis has significantly deteriorated the market quality, the J-REIT markets were resilient. Further, the introduction of Arrowhead improved the J-REIT market quality but has also increased the probability of flash crashes. Intraday patterns documented can be useful for appropriately timing trades to improve the execution quality. Finally, using difference-in-differences regression model, I show that since REITs have a higher transparency and better price discovery, they were much less affected by the financial crisis and Arrowhead as compared to non-REIT common stocks.

JEL classification: G11; G12; G14; G15

Keywords: High Frequency Trading, J-REITs, Liquidity, Volatility, Intra-day, GARCH, Arrowhead, Financial Crisis, Tokyo Stock Exchange

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1. Introduction

The explosive growth of High Frequency Trading (HFT) in recent years has intrigued several researchers. Some academics suggest that HFT is a socially beneficial financial innovation as it lowers trading costs and helps price discovery resulting in an increase in trading volume and improving liquidity (Brogaard, 2010; Chordia, Roll, and Subrahmanyam, 2008; Boehmer and Kelley, 2009; Hendershott, Jones and Menkveld, 2011). In contrast, others argue that HFT may increase volatility and systemic risk (Boehmer, Fong, and Wu, 2012; Hendershott and Moulton, 2011; Jain, Jain, and McInish, 2014). Some regulators have expressed concerns. For example, SEC Chairman Mary Schapiro mentioned in a speech on September 22, 2010, "...high frequency trading firms have a tremendous capacity to affect the stability and integrity of the equity markets. Currently, however, high frequency trading firms are subject to very little in the way of obligations either to protect that stability by promoting reasonable price continuity in tough times, or to refrain from exacerbating price volatility."

Most of the empirical research on HFT focuses on noisy proxies such as number of messages (Hendershott, Jones and Menkveld, 2011; Gai, Yao, and Ye, 2012), quotes-to-trade ratio and strategic trading (Hasbrouck and Saar, 2011).[1] This study presents a cleaner test of the impact of HFT on market quality by analyzing the introduction of a low latency trading platform, Arrowhead, by Tokyo Stock Exchange (TSE). Arrowhead increased the HFT volume from 0% to 36% within 14 months of its launch. Additionally, all the previous literature on HFT ignores

[1] Jones (2013) suggests that it is very challenging to measure the pure effect of HFT beyond other changes in equity markets.

Real Estate Investment Trusts (REITs) in their analysis. I use the introduction of Arrowhead as a natural experiment and extend the literature by analyzing the impact of HFT on REIT market quality in terms of volatility, volume, number of trades, number of quotes, quote-to-trade ratio, proportionate spreads, depth, cost-of-immediacy, and limit order book (LOB) Slope.

The fact that REITs are traded as common stocks makes them more attractive to general investors due to their potential for adding diversification to stock portfolios (Huang and Zhong 2011; Chun, Sa-Aadu, and Shilling 2004). Additionally, REITs are more liquid than traditional real estate investments; however, REITs may not necessarily be perfect substitutes for conventional equity due to their institutional features.[2] REITs are exempt from corporate income taxes but must limit their activities to owning and managing portfolios of real estate assets and pay out the bulk of their taxable income as dividends. These institutional features of REITs allow us to overcome some of the obstacles that complicate previous studies on financial crisis and HFT.

REITs are relatively straightforward value as the market value of their properties should capture most of their value (Getry, Kemsley, and Mayer, 2003). In addition, tax rules and high level of institutional ownership significantly restrict the activities REITs can undertake, so management has less impact on the value of a REIT than it has for typical industrial corporations. These unique characteristics of REITs reduce information asymmetry and lead to easier and efficient price discovery as compared to non-REIT common stocks.

I further extend the literature by analyzing the impact of financial crisis on Japanese REIT market quality. REITs' dependence on external financing can curtail their ability to exploit

[2] Specifically, the dividend distribution requirement and higher level of institutional ownership for REITs limits managerial discretion (Jensen 1986) and improves corporate governance (Chung, Fung, and Hung, 2012) implying a lower level of asymmetric information and, therefore, different risk characteristics as compared to the other common stocks (Jain, Sunderman, and Westby-Gibson, 2013; Cannon and Cole 2011; Bertin, Kofman, Michayluk, and Prather 2005).

profitable investment opportunities (Mooradian and Yang 2001).[3] This constraint is likely to be more severe during market crises (Ben-David, Franzoni, and Moussawi 2011) as during such times capital providers may withdraw their funds and force companies to liquidate their positions prematurely further deteriorating the liquidity in the market.[4] Hill, Kelly, and Hardin (2012) find that the market value of REITs holding more cash was higher during the recent financial crisis. On the other hand, Ooi, Wong, and Ong (2012) and Glascock, Michayluk, and Neuhauser (2004) find that bank lines of credit insure REITs against credit rationing at the broad market level. Therefore, these possible liquidity dry-ups may not be as prominent in REITs as compared to non-REIT common stocks. Prior research has also documented that REITs tend to have low risk, serve as an inflation hedging instrument, and have defensive stock characteristics. These features imply that REITs may behave differently than the non-REIT stocks during periods of high market volatility.[5]

The goal of this research is to analyze the impact of two different exogenous shocks on J-REIT market quality. The first shock, 2008 financial crisis, affected the investment opportunities of firms and increased the information asymmetry but kept the trading platform untouched, while the second shock, introduction of Arrowhead, enhanced the price discovery but did not affect the underlying asymmetric information. To the best of my knowledge, this is the first study that analyzes the impact of HFT and financial crisis on J-REIT market quality, and presents the intraday trading patterns for identifying optimal trading strategies.

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[3] Also see Gromb and Vayanos (2010) for a survey of literature.

[4] See Chordia, Sarkar, and Subrahmanyam (2005), Goyenko and Ukhov (2009), and Baele, Bekaert, and Inghelbrecht (2010).

[5] Glascock, Michayluk, and Neuhauser (2004) document that REITs were much less affected than non-REIT stocks by the October 27, 1997 market decline which originated in foreign exchange markets. However, the 2008 financial crisis originated in the real estate market and hence, analyzing the effect of the 2008 financial crisis on REIT market quality could provide some interesting insights. The current study extends Cannon and Cole (2011) and Jain, Sunderman, and West-by Gibson (2013) by presenting intraday patterns to identify optimal trading strategies for investors and analyzing the effect of the 2008 financial crisis and HFT on stock market quality for Japanese REITs.

2. Data, Arrowhead, and market quality measures

The sample includes all the REITs listed on TSE from their inception in 2001 to December 2012. The data on market value, daily prices, trading volume, and bid- and ask-prices are obtained from Datastream. The ticker symbols for all REITs derived from Datastream database are cross-referenced with the listing provided on the TSE website.[6] The high frequency data on intraday prices, trading volume, top 10 best bid and ask quotes, and the respective volume supplied at each of the 10 levels, for every minute of trading for all the REITs listed on the TSE for months January 2008, January 2009, and January 2011, are obtained from Nikkei Digital Media Inc.'s Nikkei Economic Electronic Database Systems (NEEDS) database.[7] TSE trading takes place in two different trading sessions. The morning session begins at 9:00 a.m. and ends at 11:00 a.m., while the afternoon session begins at 12:30 p.m. and ends at 3 p.m. Both limit and market orders are permitted. TSE has tiered minimum tick sizes, price limits, and minimum trading unit that varies with the stock's price.

Historically the TSE had provisions for warning quotes, which are automated non-tradable indicative quotes placed by the exchange to smooth the price movements. These frequent warning quotes were abandoned on August 24, 1998. TSE also has provisions for special quotes that arise in situations similar to those that trigger a warning quote, but with multiple orders on the active side of the LOB. To account for these special quotes I conduct the analyses with and without these special quotes. I incorporate these special features of TSE in the main analysis as well as conduct several robustness tests to ensure that the results can be generalized beyond the TSE. Additionally, there are no hidden orders on TSE, which allows for cleaner predictions. Following Jain, Jain, and McInish (2014), I remove trades outside of regular

[6] http://www.tse.or.jp/english/rules/reits/list.html

[7] For intraday analyses, I analyze three month of data due to computational limitations. Each month of data is about 125 GB with over 100 billion observations; simple sorting and estimation of cross-correlation takes over 3 weeks.

trading hours and trades with zero prices or zero volume, quotes with bid greater than ask, and limit orders with zero limit price.

2.1. Arrowhead low latency trading platform

On January 4, 2010, the TSE launched a new, high-tech trading platform called "Arrowhead," that cost about $142 million. With the new low latency Arrowhead trading platform, the TSE can process trades in two milliseconds (time elapsed between order placement and order execution), which is at least 6,000 times faster than their previous trading platform (TSE Fact book, 2011). Arrowhead has reduced latency by eliminating the matching cycle delay, executing orders immediately, and instantaneously updating the LOB (Uno and Shibata, 2011). The new platform was introduced to attract investors who depend on sophisticated software to make split-second trades. [8] Unlike the other developed markets, such as the US, Japanese stock market is not fragmented and any given stock can only be traded on one exchange, which helps us make cleaner predictions.

2.2. Liquidity Measures

Kyle (1985) suggests "Liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets, these include tightness, depth, and resiliency.'' This definition encompasses three components of liquidity – tightness, depth and resiliency. Tightness is the distance between the bid and ask quotes. Depth, defined as the total volume supplied by the composite orders in a LOB, and resiliency represents how quickly the market can return back to its original state after a shock. I analyze the following liquidity variables:

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[8] Hamao, Masulis and Ng (1990), Chan, Hamao and Lakonishok (1991) Lehmann and Modest (1994), Hamao and Hasbrouck (1995), and Bremer, Hiraki, and Sweeney (1997), Ahn, Hamao and Ho (2002) analyze different special features of TSE, such as expected returns, minimum trading unit, price limits, and warning quotes before the introduction of Arrowhead and for non-REIT common stocks.

Volume

Trading volume, most recently studied by Bertin, Kofman, Michayluck and Prather (2005), has also been revealed as significant activity-based measures of liquidity. I base my analysis of volume on the number of trades, because Jones, Kaul and Lipson (1994) find that this is a better measure of information asymmetry. In addition, I also analyze the average trade size and trading volume.

Spreads

Quoted spreads (SPRD) and proportionate spreads (PSPRD) are the most commonly used measures of liquidity. I calculate both of these measures at the end of every minute of trading. Let Ask_i be the best ask quote and Bid_i be the best bid quote for minute i. *SPRD* and *PSRD* are calculated as follows:

$$Quoted\ Spread\ =\ Sprd\ =\ Ask_i - Bid_i \tag{1}$$

$$Relative\ Spread = Rsprd = \frac{(Ask_i - Bid_i)}{\left(\frac{Ask_i + Bid_i}{2}\right)} \tag{2}$$

But these traditional measures based on top of the LOB do not present a comprehensive assessment of LOB liquidity because buy and sell orders can cluster away from the best bid and ask prices (Rosu, 2009; Goettler, Parlour, and Rajan, 2005). The importance of liquidity away from the best bid and ask in high-frequency markets is highlighted by Jain, Jain, and McInish (2014), Jain and Jiang (2014), and Aitken, Almeida, Harris, and McInish (2007) who document that traders provide liquidity simultaneously at multiple prices. Therefore, in addition to the above mentioned traditional liquidity measures, I also examine a couple of newer liquidity measures that quantify the state of the LOB beyond the best quotes: LOB Slope and Cost of

Immediacy (COI). Change in the LOB Slope measures resiliency of the full LOB while COI measures the tightness and depth of the LOB (Jain, Jain, and McInish, 2014).

LOB slope

The LOB Slope describes how the quantity supplied in the LOB changes with price (Biais, Hillion, and Spatt, 1995). A higher value of LOB Slope suggests that a market can absorb large demands with very little price impact. Hence, a steeper LOB Slope represents liquid markets. Following Naes and Skjeltorp (2006), I measure the LOB slope for firm *i* at time *t*, as follows:

$$SLOPE_{i,t} = \frac{BIDSLOPE_{i,t} + ASKSLOPE_{i,t}}{2} \tag{3}$$

where $BIDSLOPE_{i,t}$ and $ASKSLOPE_{i,t}$ represent the slope of the bid and ask side, respectively. The LOB slope for the bid side for firm *i* at time *t*, is given as:

$$BIDSLOPE_{i,t} = \frac{1}{N_B}\left\{\frac{v_1^B}{|p_1^B/p_0 - 1|} + \sum_{\tau=1}^{N_B-1}\frac{\frac{v_{\tau+1}^B}{v_\tau^B} - 1}{|p_{\tau+1}^B/p_\tau^B - 1|}\right\} \tag{4}$$

Similarly, the LOB slope for the ask side can be given as:

$$ASKSLOPE_{i,t} = \frac{1}{N_A}\left\{\frac{v_1^A}{|p_1^A/p_0 - 1|} + \sum_{\tau=1}^{N_A-1}\frac{v_{\tau+1}^A/v_\tau^A - 1}{|p_{\tau+1}^A/p_\tau^A - 1|}\right\} \tag{5}$$

where N_B and N_A are the total number of bid and ask orders, respectively. τ denotes tick levels, with $\tau = 0$ representing the best bid-ask mid-point and $\tau > 0$ representing the subsequent ask (bid) quote with positive share volume. p_0 is the best bid-ask mid-point and v_τ^A and v_τ^B is the natural logarithm of accumulated total share volume at the price level $p_\tau^A$and p_τ^B, respectively. In other words, v_τ^A (v_τ^B) is the natural logarithm of cumulative share volume supplied (demanded) at

p_τ^A (p_τ^B) or lower (higher). At the end of each minute, I use the ten best bid and ask quotes together with the share volume at these quotes for the calculation of the LOB slope.

The cost-of-immediacy (COI)

A deep LOB can absorb a sudden surge in the demand of liquidity with minimal price impact. A large marketable buy (sell) order is first executed against the best ask (bid) and then subsequently climb up (walk down) the book for execution of the remaining volume at inferior prices (Jain and Jiang, 2014). The further that marketable order walks up or down the book, the larger is the difference between the execution price and the mid-quote, and, therefore, the more costly the trading process will be for the impatient market order traders (Jain, Jain, and McInish, 2014).

For each stock I estimate the impact of a sudden surge in the demand for liquidity, or COI, separately on the buy and the sell sides, equivalent to 1% of average daily trading volume. Let *T* be the total number of shares to be bought or sold. I denote the j^{th} best bid (ask) price as P_j^{Buy} (P_j^{Sell}) and the *jth* best bid (ask) size as Q_j^{Buy} (Q_j^{Sell}). I define two indicator variables, I_k^{Buy} and I_k^{Sell}, which refer to number of shares bought or sold respectively at each price point, *k*.

$$I_k^{Buy} = \begin{cases} Q_j^{Buy} & if\ T > \sum_{j=1}^{k} Q_j^{Buy} \\ \left(T - \sum_{j=1}^{k-1} Q_j^{Buy}\right) & if\ T > \sum_{j=1}^{k-1} Q_j^{Buy}\ and\ T < \sum_{j=1}^{k} Q_j^{Buy} \\ 0 & otherwise \end{cases}$$

$$I_k^{Sell} = \begin{cases} Q_j^{Sell} & if\ T > \sum_{j=1}^{k} Q_j^{Sell} \\ \left(T - \sum_{j=1}^{k-1} Q_j^{Sell}\right) & if\ T > \sum_{j=1}^{k-1} Q_j^{Sell}\ and\ T < \sum_{j=1}^{k} Q_j^{Sell} \\ 0 & otherwise \end{cases}$$

Then, I compute the (round-trip) cost-to-trade for stock *i* as the proportion of the trading cost calculated above to the fair value of the trade, which is estimated by multiplying the total number of shares to be traded with the best bid offer mid-quote price level:

$$Cost - to - Trade_i = \frac{\sum_{k=1}^{5} I_k^{Buy}\left(Midquote - p_k^{Buy}\right) + \sum_{k=1}^{5} I_k^{Sell}\left(p_k^{Sell} - Midquote\right)}{T \times Midquote} \qquad (6)$$

2.3. Volatility Measures

I compute the volatility measure following the auto-regressive model proposed by Schwert (1989). I use the following regression model to measure the unexpected return:

$$R_t = \sum_{k=1}^{5} \propto_k D_k + \sum_{j=1}^{12} \beta_j R_{t-j} + \varepsilon_t \qquad (7)$$

where, R_t is the return on a stock for time t, and D_k is a day-of-the-week dummy for day *k*. To avoid measurement errors due to the bid-ask bounce, I calculate returns from the average of bid-ask prices (mid-quote) at the end of each minute of trading. The 12 lagged returns are included to account for short-term movements in conditional expected returns. The absolute value of the residual, ε_t, serves as a measure of volatility for a stock for minute *t*.[9]

[9] I test the robustness of the results using the standard deviation of returns as a volatility measure.

3. REITs market in Japan

The REITs were introduced in Japan during 2001, which also marked the introduction of REITs in Asia.[10] Japan REITs (J-REITs) market is the largest REITs market in the Asia. Table 1 presents the descriptive statistics for J-REITs using the daily data since their inception. Table 1 and Figure 1 Panel A show that the first 2 J-REITs were listed on TSE on September 10, 2001. Since then the market value of REITs grew rapidly to over $50 billion with 40 listed J-REITs during the peak period of mid-2007 (Figure 1, Panel B). J-REITs lost more than half of their value during the 2008 financial crisis, reducing the net market value to less than $20 billion by March 2009. Figure 1, Panel B and Table 1 further show that the J-REIT market has seen a consistent growth during the post-crisis period with market value of listed J-REITs increasing to over $30 billion by the end of 2012.

Figure 2 presents J-REITs daily return and volatility. We observe that the returns were mostly positive during the pre-crisis and post-crisis periods and negative during the 2008 financial crisis period. Table 1 reports the average daily returns were -0.13% and -0.15% during the years 2008 and 2009, respectively. We also observe that J-REITs were extremely volatile during the crisis period. The volatility peaked during October of 2008. Table 1 further report that the average daily return volatility during 2008 and 2009 was 3.70% and 2.71%, respectively, which was much higher than other years.

Figure 3 shows that J-REIT volume has been consistently increasing since their inception. Figure 4 shows that J-REIT liquidity deteriorated significantly during the crisis period as documented by the increased proportionate spreads. These results document that the market conditions for J-REITs have changed significantly since 2008. To assess the impact of HFT on REIT market quality and to fully document the effect of crisis, one needs to consider high

[10] For more details about J-REITs, see: http://www.ares.or.jp/jrem/jres/pdf/k_jreit_int_5.pdf

frequency data. The daily data do not capture the changes in the intra-day variations caused due to the increase in HFT (Jain, Jain, and McInish, 2014; Jain, Sunderman, and Westby-Gibson, 2013), hence, in the next sections I present the results of intraday analyses using minute-by-minute trading data.

4. High frequency analyses

I analyze the evolution of key market quality parameters, such as, liquidity, volatility, volume, number of trades, and quotes-to-trade ratio across a trading day by dividing the trading day into 54 five-minute intervals. Table 2 presents the descriptive statistics for the key market quality parameters calculated at the five-minute frequency for the full sample period and across the three sub-periods: pre-crisis, crisis, and post-Arrowhead. The last 2 columns report the differences in means across the sub-samples. Statistical inference is conducted using Thompson (2009) standard errors. I find that five-minute returns significantly declined during the crisis period and increased during the post-Arrowhead period. I also find that volatility significantly increased during the crisis period. Introduction of Arrowhead significantly reduced the volatility by 70% from its crisis period level of 0.13% and by 64% from its pre-crisis period level of 0.11%. Hence, HFT helps reducing the volatility for J-REITs. The results support the theoretical predictions of Foucault, Kadan and Kandel (2005), Baruch (2005), and Boehmer, Saar and Yu (2005) who suggest that the higher speed of trading can increase the competition among liquidity suppliers at various price points that dampens the short-term volatility. Figure 4 graphically presents this result.

Table 2 and Figure 5 show that the trading volume significantly declined by 32% during the crisis period and increased by 43% during the post-Arrowhead period from its pre-crisis level of 7.99 stocks per five-minute of trading. I further find that the average trade size declined, while the number of trades and number of quotes significantly increased during the crisis period. These results suggest that the investors were cautiously submitting smaller orders and continually updating their expectations by revising the submitted orders during the crisis period. The results also show that the number of trades increased by almost 50% while the average trade size reduced by 2% during the post-Arrowhead period as compared to their pre-crisis level. The most dramatic increase is observed in the number of quotes which increased by 124% during the post-Arrowhead period from its pre-crisis level of 5.51 quotes per five-minutes of trading. This result is in line with the "quote stuffing" literature that documents a significant increase in the superficial order flow due to the increase in HFT (Egginton, Van Ness, and Van Ness, 2013; Golub, Keane, and Poon, 2012; Gai, Yao, and Ye, 2012; Biais and Woolley, 2011). Figures 6 and 7 graphically summarize these results. However, the number of quotes can increase for price efficiency reasons such as speedier incorporation of fundamental information into prices through aggressive quote revisions (Jain, Jain, and McInish, 2014). Hence, I calculate quotes-to-trade ratio to capture the dynamics of liquidity suppliers and demanders. I find that, although the quotes-to-trade ratio increased by 50% during the post-Arrowhead period, the increase is not as dramatic as the increase in the number of quotes.

Table 2 further reports that liquidity deteriorated during the crisis period as reflected by the higher proportionate spreads and lower depth. Figures 8 and 9 show that proportionate spreads reduced dramatically during the post-Arrowhead period, however, the depth also decreased by over 50% suggesting that, while HFT increased liquidity by reducing the cost of trading, it might have also increased the probability of flash crashes due to reduced depth.

The above results are derived using trading data or just the top of the limit order book (LOB) information. However, Aitken, Almeida, Harris, and McInish (2007), Goettler, Parlour, and Rajan (2005), and Rosu (2009) highlights the importance of multiple price levels away from the best bid and ask in high-frequency markets. Hence, Figures 10 and 11 examine a couple of newer liquidity measures that quantify the state of the LOB beyond the best quotes. Surprisingly, we observe that both LOB Slope and COI increased during the crisis period.[11] This suggests that while it was costly to trade during the crisis period, the J-REIT market was resilient. This is the first study to document this behavior of the crisis period. We also observe that Arrowhead significantly improved the LOB liquidity, by increasing LOB Slope and reducing COI. Table 2 further reports that ask-side of LOB is more liquid than bid-side, which suggest that the cost to sell is higher than the cost to buy.

5. Intraday Analyses

In this section, I present the intraday patterns for each of the market quality parameters during the pre-crisis, crisis, and post-Arrowhead periods, by dividing the trading day into 270 one-minute intervals. For most of the liquidity and volatility measures, we observe the well-established U-shape patterns (see McInish and Wood, 1992) during all the three sub-periods.

Figure 12 presents the intraday patterns for volatility. We observe a U-shape pattern during the first trading session while a J-shape pattern during the second trading session for the pre-crisis period. In general, the volatility is lower during the second trading session. During the crisis period we observe a U-shape pattern across the entire trading day. Volatility is higher during the start and the end of the trading day and lower around the recess period. We also observe that volatility declined significantly during the post-Arrowhead period, with the end of

[11] LOB Slope is a direct measure of LOB liquidity, while COI is an inverse measure of liquidity.

the trading day experiencing the highest volatility. This is consistent with the notion that HFT typically end the day with zero holdings. Hence, the higher volatility during the end of the day may reflect aggressive trading by HFT during that period.

Figure 13 presents the intraday patterns for trading volume. We observe that for all the three sub-periods, volume is higher during the opening and closing of a trading day. Volume significantly declined during the crisis period and increased during the post-Arrowhead period. The U-shape patterns during the two trading sessions are much more prominent during the post-Arrowhead period.

Figures 14 and 15 illustrate the intraday patterns for number of trades and number of quotes, respectively. We observe that during all the three sub periods number of trades and number of quotes are largest at the end of the trading day. While the number of trades during the crisis period declined significantly, the number of quotes remained about the same as compared to the pre-crisis period. This suggests that traders were continually revising or cancelling their orders during the crisis period, to avoid the pick-off risk. Both, the number of trades and number of quotes increased dramatically during the post-Arrowhead period. We also observe a prominent U-shape pattern during the two trading sessions for the post-Arrowhead period. Number of quotes at the start of each of the trading sessions, is lower for both, the pre-crisis and crisis periods, reflecting that more quotes were executed (rather than revised) during that time frame. However, during the post-arrowhead period we observe significantly higher number of quotes during the open and close of the trading day. This may be due to the "quote stuffing" trading strategy of the HFTs, which involves submitting an unwieldy number of orders to the market to generate congestion. This slows down the other market participants giving an advantage to the HFT submitting such superficial order flow.

The above results are well supported by Figure 16 which documents the intraday patterns for quotes-to-trade ratio (QTR). During both, the pre-crisis and the crisis periods, we observe a lower QTR during the start of the day supporting the argument that during this period the execution probability of an order is very high. However, during the post-Arrowhead period the QTR is higher during the open and close of a trading day. Additionally, we observe a significant increase in QTR during the post-Arrowhead period indicating the use “quote stuffing” trading strategy by HFTs.

Figures 17 and 18 present the intraday patterns for the top of the LOB liquidity variables: proportionate spreads and depth. We observe a U-shape pattern for proportionate spreads during both the trading sessions across all three sub-periods. We also observe that the spreads declined significantly during the post-Arrowhead period, reflecting an increase in liquidity. This result is consistent with the findings of Hendershott, Jones, and Menkveld (2011). Next we observe that markets are deep during the first few minutes of trading during all the three sub periods. I also find that depth is higher during the second trading session during the entire sample period. Finally, we see that the depth declined significantly during the crisis period. Depth also declined during the post-Arrowhead period reflecting an increase in the probability of flash crash.

To present a comprehensive assessment of LOB liquidity, Figures 19 and 20 illustrates the intraday patterns for LOB Slope and COI. We observe an inverse U-shape pattern for LOB Slope and a U-shape pattern for COI during the two trading sessions across the three sub-periods. I also find that LOB Slope significantly increased while COI significantly decreased during the post-Arrowhead period. These observations support the theoretical predictions of Foucault, Kadan and Kandel (2005), Baruch (2005), and Boehmer, Saar and Yu (2005). Higher speed of trading can increase the competition among liquidity suppliers at various price points that, in turn, should reduce the cost of immediacy for liquidity demanders.

6. Regression analysis

Following Stoll (2000) model I formally test the evolution of liquidity during the crisis and the post-Arrowhead periods. Market orders demand liquidity while limit orders supply liquidity. The liquidity demanders have to incur a cost for immediate trading due to the market frictions. These frictions can be measured by the price premium paid by a liquidity demander for an immediate transaction (Demsetz 1968; Stoll 2000). Stoll (2000) model the cross-sectional relation of trading costs to firms' trading characteristics in the following form:

$$RSPRD = \propto_0 + \beta_1 LogVOL + \beta_2 LogNTRD + \beta_3 LogMV + \beta_4 LogPRICE + \beta_5 PRIVAR + \varepsilon \quad (8)$$

where *RSPRD* is the relative spreads, *VOL* is the volume traded, *NTRD* is the number of trades, *MV* is the stock's market value, *PRICE* is the stock's price, *PRIVAR* is the price volatility, and ε is the error term.[12]

To formally test the differences in liquidity across the three sub-periods, I add two dummy variables: *CRISIS*, to capture the impact of recent financial crisis on liquidity, and *ARROWHEAD*, to capture the effect of HFT on liquidity. *CRISIS* takes a value of 1 for the crisis period of January 2009, zero, otherwise. *ARROWHEAD* takes a value of 1 for the post-Arrowhead period of January 2011, zero, otherwise. Additionally, to account for the trading costs for entire LOB, COI (or LOB SLOPE) serves as the dependent variable. The final regression model takes following form:

$$COI\ or\ LOB\ SLOPE = \propto_0 + \beta_1 ARROWHEAD + \beta_2 CRISIS + \beta_3 Log\ VOL + \beta_4 Log\ NTRD$$

[12] Danielsen and Harrison (2000) find that determinants of REIT liquidity vary depending on the exchange where the security is listed. Since, this study analyzes J-REITs which are listed only on TSE, I do not need to control for differences in market structures.

$$+ \beta_5 Log\ MV\ + \beta_6 Log\ PRICE + \beta_7 PRIVAR + \varepsilon \qquad (9)$$

where *COI* (=*ASKCOI*+ *BIDCOI*) measures the cost that liquidity demanders have to bear above the intrinsic value due to a sudden surge in the demand for 1% of the daily average trading volume. LOB Slope for the five best asks (*ASKSLOPE*) and five best bids (*BIDSLOPE*) is calculated using Equations 4 and 5, respectively. *SLOPE* is (*BIDSLOPE* + *ASKSLOPE*)/2. COI is an inverse measure of LOB liquidity while LOB SLOPE is a direct measure of LOB liquidity.

Results from this analysis are summarized in Table 3. The first 2 models present the results for COI liquidity variable while the next 2 models present the results for LOB Slope liquidity measure. Statistical inference is conducted using Thompson (2009) standard errors. This technique allows for both time-series and cross-sectional correlation of the regression errors, as well as heteroskedasticity. I find that LOB liquidity is positively related to measures of trading activity, such as volume (*LOG VOL)* and number of trades (*LOG NTRDS*), and negatively related to stock's volatility (*PRIVAR*). Hence, stocks with higher trading volume and number of trades, and lower volatility have lower COI and higher LOB SLOPE. I also find that LOB liquidity is higher for larger firms and firms with higher prices. These results are consistent with Stoll (2000) and Cannon and Cole (2011).

Table 3 also reports a significant and negative (positive) coefficient -0.05 (0.09) for ARROWHEAD for COI (LOB SLOPE) regression model, suggesting that Arrowhead has significantly improved the LOB liquidity. I also find a positive and statistically significant coefficient for CRISIS in the COI regression model. This result suggests that the cost of instantaneous trading significantly increased during the crisis period and has significantly declined during the post-Arrowhead period.

7. GARCH analysis

Table 2 shows that the volatility increased during the crisis period and declined during the post-Arrowhead period. I formally test this volatility difference using several GARH models. I control for various factors proposed in the literature that can explain volatility: Spreads (Hasbrouck 1999), Depth (Ahn, Bae, and Chan 2001), Trading Volume (Gallant, Rossi, and Tauchen 1992), Number of Trades (Jones, Kaul and Lipson 1994), and Monday, to control for the weekend effect, (French 1980; Foster and Viswanathan 1990).

Following Jain and Jiang (2014), I use two different model specifications to analyze the effect of Arrowhead and recent financial crisis on volatility. First, I consider the following two stage auto-regressive model proposed by Schwert, 1989. In the first stage the unexpected return is estimated using the following regression model:

$$R_t = \sum_{k=1}^{5} \propto_k D_k + \sum_{j=1}^{12} \beta_j R_{t-j} + \varepsilon_t \qquad (10)$$

where, R_t is the return on a stock for time t, and D_k is a day-of-the-week dummy for day k. To avoid measurement errors due to the bid-ask bounce, I calculate returns from the average of bid-ask prices (mid-quote) at the end of each minute of trading. The 12 lagged returns are included to account for short-term movements in conditional expected returns. The absolute value of the residual, ε_t, constitute the estimate of the volatility for a stock at time t.

In the second stage I run the following regression model:

$$|\varepsilon_{i,t}| = \alpha_0 + \beta_1 ARROWHEAD_{\mathrm{t}} + \beta_2 CRISIS_{\mathrm{t}} + \beta_3 RSPRD_{\mathrm{t}} + \beta_4 DEPTH_{\mathrm{t}} + \beta_5 VOL_{\mathrm{t}} +$$

$$\beta_6 NTRD_{\mathrm{t}} + \beta_7 M_{\mathrm{t}} + \sum_{j=1}^{12} \delta_{i,j} |\varepsilon_{i,t-j}| + \mu_{i,t+1} \qquad (11)$$

where *ARROWHEAD* is a dummy variable that takes a value of 1 for the post-Arrowhead period of January 2011, zero, otherwise, *CRISIS* is a dummy variable that takes a value of 1 for the crisis period of January 2009, zero, otherwise, *RSPRD* is the time relative spread, *DEPTH* is the average volume supplied at the best bid and best ask, *ATS* is the average trade size, *VOL* is the volume traded, *NTRD* is the number of trades for each minute of trading, *M* is a dummy variable that is equal to 1 for Mondays and 0 otherwise, and ε_t is the residual from the return equation. The parameter δ captures the persistence in volatility.

Pagan and Ullah (1988) argue that the true volatility is unobservable and hence, the above two stage estimation, using equations (10) and (11), leads to inconsistent estimates. Also the two stage OLS model do not account for volatility clustering observed in the data (Bollerslev and Domowitz, 1991). So, to take care of these econometric problem, I use the following GARCH(1,1) specification:

$$R_t = \sum_{k=1}^{5} \propto_k D_k + \sum_{j=1}^{12} \beta_j R_{t-j} + \varepsilon_t \tag{12}$$

$$\sigma_t^2 = \alpha_0 + \beta_1 ARROWHEAD_t + \beta_2 CRISIS_t + \beta_3 RSPRD_t + \beta_4 DEPTH_t + \beta_5 VOL_t + \beta_6 NTRD_t + \beta_7 M_t + \alpha_1 \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \tag{13}$$

Both the equations are estimated simultaneously as one system. The variables are as defined previously. The selection of GARCH(1,1) model is based on the lowest AIC and SIC values.

I conduct the analysis using both the above mentioned model specifications. Since, the results from the two models are qualitatively similar, I present only the results from GARCH(1,1) analysis.

Table 4 summarizes the results from the estimation of the various GARCH(1,1) models presented by equations (12) and (13), using the high frequency minute-by-minute data for all J-REITs. Models 1, 3, and 4, show that ARROWHEAD has significantly reduced the volatility for J-REITs. Models 2, 3 and 4, show that CRISIS has significantly increased the volatility for the J-REITs. I also find a positive and statistically significant coefficient for NTRD, which suggests that informed trader camouflages his trading activity by splitting one large trade into several small trades (Kyle 1985; Admati and Pfleiderer 1988). Hence, number of trades conveys private information as reflected by increased volatility (Jones, Kaul, and Lipson 1994). Additionally, I find a positive and statistically significant coefficient for RSPRD. This result suggests that the highly liquid market can accommodate large liquidity demands resulting in a smoother price formation which lowers volatility.

8. Difference-in-differences analysis

If REITs have lower information asymmetry and easier and efficient price discovery as compared to non-REIT common stocks, then REITs should experience a significantly lower impact of 2008 financial crisis, which increased the information asymmetry, and introduction of Arrowhead, with improved the price discovery. To test this argument, I conduct a difference-in-differences regression analysis for the liquidity and volatility measures. Non-REIT common stocks listed on the TSE, matched with J-REIT sample stock based on market capitalization, serves as a control sample.[13] The sample for the tests includes pre-crisis period of January 2007, crisis period of January 2009, and post-Arrowhead period of January 2011. I limit the observations to three months both to keep the analysis more manageable and to mitigate the serial correlation bias from difference-in-differences approaches (Bertrand, Duflo, and Mullainathan, 2004). The difference-in-differences regression is as follows:

$$Y = \propto_0 + \mu + \beta_1 ARROW + \beta_2 CRISIS + \beta_3 ARROW * REIT + \beta_4 CRISIS * REIT + \beta_5 \boldsymbol{X} + \varepsilon \quad (14)$$

where Y is the market quality variable of interest (e.g., SLOPE, COI, or VOLATILITY), μ is the firm-specific effect, *ARROW* is an indicator variable that takes a value of 1 for the post-

[13] I test the robustness of findings by matching stocks based on book to market ratio and based on market cap and book to market ratio.

Arrowhead period, zero otherwise, *CRISIS* is a dummy variable that takes a value of 1 for the crisis period, zero otherwise, *REIT* is an indicator variable that takes a value of 1 for REIT common stock and zero for a market capitalization matched non-REIT common stock, and *X* is a set of control variables used in the previous analyses (including a REIT dummy variable is unnecessary in this framework specifically because we include firm fixed effects).

Table 5 reports the results from the difference-in-differences regression analysis. The first two columns summarize the results from tests with one of the LOB liquidity measures as the outcome variable. The positive (negative) and significant coefficient for *ARROW***REIT* indicates that the impact of the launch of Arrowhead on REIT's COI (SLOPE) was significantly lower than the non-REITs. Last column in Table 5 reports similar findings for volatility. These results suggest that since RIETs already have a very efficient price discovery process, they benefit less as compared to the non-REITs, from the trading platform overhaul that improved the price discovery.

Similarly, the negative (positive) and significant coefficient for *ARROW*CRISIS* indicates that the impact of 2008 financial crisis on REIT's COI (SLOPE) and volatility was significantly lower than the non-REITs. Due to the ease of valuation and other unique institutional features discussed earlier, REITs have lower information asymmetry as compared to non-REITs. Hence, REITs were much less affected, as compared to non-REITs, by the 2008 financial crisis which significantly increased the information asymmetry.

9. Robustness Tests

I test the robustness of the results after accounting for the effect of intraday seasonality. I include 2 dummy variables to control for the opening and closing of each of the two sessions.

The first dummy variable takes a value of 1 for the first half hour (9:00 AM-9:30 AM) and last half hour (2:30 PM- 3:00 PM) of trading, zero otherwise. The second dummy variable takes a value of 1 for the last half hour (10:30 AM-11:00 AM) of trading right before the recess and first half hour (2:30 PM- 3:00 PM) of trading right after the recess, zero otherwise. Although, I find a statistically significant coefficient for the 2 dummy variables, which suggest the presences of the intraday seasonality in liquidity and volatility, but the results for the effect of Arrowhead and crisis are qualitatively similar to the ones presented earlier in terms of direction and level of significance.

The TSE has a provision of special quotes, which are automated non-tradable indicative quotes placed by the exchange to advertise potential jumps in price and to encourage investors to place balancing orders on the other side. I delete these special quotes and find results consistent with the ones summarized in the previous section.

During 2010, 6 J-REITs got delisted. I tested the robustness of my results by removing these delisted J-REITs and find the results consistent with the ones presented earlier.

9. Conclusion

In this study I summarize the history of various market quality parameters for the REITs (J-REITs) listed on the Tokyo Stock Exchange (TSE) since their inception in 2001. Using the introduction of the Arrowhead low latency trading platform by the TSE as a natural experiment, I analyze the impact of high frequency trading (HFT) on market quality, in terms of volatility, volume, number of trades, number of quotes, quote-to-trade ratio, proportionate spreads, and depth. Further, to present the comprehensive assessment of limit order book (LOB) liquidity for J-REITs, I analyze two newer LOB liquidity measures: cost-of-immediacy (COI), and LOB

Slope. In addition, I assess the impact of the recent financial crisis on J-REITs market quality. I also present the intraday patterns for these key parameters and conduct the regression and GARCH analyses to formally test the impact of Arrowhead and recent financial crisis on market quality. Finally, I document that since REITs have lower informational asymmetry and better price discovery, they were much less affected by the financial crisis and the introduction of Arrowhead as compared to non-REIT common stocks.

I show that the J-REIT market grew significantly until late 2007. J-REIT market value started falling with markets becoming more volatile and reached its trough during October of 2008. Since then J-REITs have seen significant growth. To conduct a cleaner test of the impact of HFT and on REIT market quality and to fully document the effect of crisis, I present high frequency minute-by-minute analyses of the key market quality parameters.

I find that volatility, number of trades, number of quotes, proportionate spreads, COI and LOB slope increased, while the trading volume and depth declined during the crisis period. These results document that while the financial crisis significantly worsened J-REIT market quality, markets were resilient during that period. Further, I document that the trading volume, number of trades, number of quotes, quote-to-trade ratio, and LOB Slope increased, while volatility, proportionate spreads, depth, and COI declined during the post-Arrowhead period. Hence, the introduction of low latency trading system on TSE improved the J-REIT market quality by increasing liquidity and reducing volatility. But Arrowhead might have also increased the probability of flash crashes due to significant reduction in depth. I also find that Arrowhead has generated incentives for traders to use the "quote stuffing" trading strategies as reflected by the increased QTR. I also document significant changes in the intraday patterns for various market quality parameters during the crisis and post-Arrowhead periods. The intraday patterns suggest that by appropriately timing the trades, a trader can minimize the transaction costs and improve the execution quality. Finally, using difference-in-differences analysis technique, I document that REITs were much less affected by the two exogenous shocks: financial crisis, which increased the information asymmetry, and launch of Arrowhead, which improved the price discovery process; as compared to non-REIT common stocks.

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Table 1.

Summary statistics across years

This table presents the number of J-REITs listed on Tokyo Stock Exchange and their respective market value across years since their inception. I also report the daily return, volatility, volume, and proportionate spreads.

Year	**Number of J-REITs**	**Market Value (in million $)**	**Return**	**Volatility**	**Volume**	**Proportionate Spreads**
2001	2	729.47	-0.19%	1.11%	61100	0.53%
2002	6	4316.87	0.07%	0.88%	546300	0.45%
2003	10	7537.87	0.04%	0.75%	1242000	0.35%
2004	14	16015.64	0.10%	0.83%	2466200	0.33%
2005	27	26035.43	0.02%	0.86%	3619700	0.44%
2006	38	35920.14	0.06%	1.31%	4068400	0.68%
2007	40	50765.17	0.03%	2.37%	7077900	0.91%
2008	39	34147.10	-0.13%	3.70%	6853800	0.98%
2009	40	21739.10	-0.15%	2.71%	5308600	0.79%
2010	35	27271.72	0.07%	1.60%	5175800	0.57%
2011	42	30135.51	-0.06%	1.35%	5862700	0.49%
2012	45	30802.35	0.08%	1.10%	6089200	0.41%
2013	48	3128.44	0.42%	1.35%	695500	0.38%

Table 2.

Summary statistics

This table reports the means for various market quality measures for the full sample period and across the three sub-periods: pre-crisis (January 2008), crisis (January 2009), and post-Arrowhead (January 2011). All the variables are calculated at a 5 minute frequency. Means are reported for: *Return*, which is logged changes in quote mid-point, *Volatility*, which is the absolute value of the error term from the return equation (7), *Volume*, which is the number of shares traded, *Average trade size*, which is the number of shares traded per trade, *Number of Trades*, *Number of Quotes*, *Quotes-to-trade* ratio, which is the number of quotes divided by the number of trades, *Proportionate Spread*, *Depth* at the best quotes, LOB Slope for the five best asks (*ASKSLOPE*) and five best bids (*BIDSLOPE*) is calculated using Equations 4 and 5, respectively. *SLOPE* is (*BIDSLOPE* + *ASKSLOPE*)/2, and *COI* (=*ASKCOI*+ *BIDCOI*) measures the cost that liquidity demanders have to bear above the intrinsic value due to a sudden surge in the demand for 1% of the daily average trading volume. The last two columns present the differences in means across the three sub-periods to assess the impact of crisis and HFT. Thompson (2011) standard errors are reported in parentheses below the coefficient estimates.

Panel A. Traditional Measures

Variable	**Full sample**	**Pre-Crisis**	**Crisis**	**Post-Arrowhead**	**Crisis – Pre-crisis**	**Arrowhead – Pre-crisis**
Return	-0.0014%	-0.0017%	-0.0023%	-0.0001%	-0.0006%*	0.0016%*
					(0.00)	(0.00)
Volatility	0.10%	0.11%	0.13%	0.04%	0.02%*	-0.07%*
					(0.01)	(0.02)
Volume	8.29	7.99	5.44	11.45	-2.55*	3.46*
					(1.02)	(0.89)
Average Trade Size	3.08	3.51	2.27	3.45	-1.24*	-0.06*
					(0.27)	(0.03)
Number of Trades	2.42	2.01	2.35	3.00	0.34*	0.99*
					(0.13)	(0.19)
Number of Quotes	7.93	5.51	5.97	12.32	0.46	6.81*
					(0.31)	(0.95)
Quotes-to-Trade ratio	3.28	2.74	2.64	4.11	-0.10	1.37*
					(0.09)	(0.15)
Proportionate Spread	0.45%	0.56%	0.60%	0.19%	0.04%*	-0.37%*
					(0.01)	(0.09)
Depth	16.03	29.73	4.81	13.54	-24.92*	-16.19*
					(3.49)	(2.64)

Panel B. Advanced LOB liquidity measures

Variable	Full sample	Pre-Crisis	Crisis	Post-Arrowhead	Crisis – Pre-crisis	Arrowhead – Pre-crisis
BIDSLOPE	503.76	314.52	394.40	802.35	79.88*	487.83*
					(5.44)	(8.01)
ASKSLOPE	512.27	313.03	390.50	833.29	77.47*	520.26*
					(5.63)	(8.12)
LOB Slope	518.98	313.09	400.18	843.66	87.09*	530.57*
					(5.49)	(8.08)
ASKCOI	0.35%	0.42%	0.46%	0.18%	0.04%*	-0.24%*
					(0.02)	(0.05)
BIDCOI	0.37%	0.43%	0.49%	0.18%	0.06%*	-0.25%*
					(0.02)	(0.06)
COI	0.72%	0.84%	0.96%	0.35%	0.12%*	-0.49%*
					(0.03)	(0.08)

* Significant at 5% level

Table 3.

LOB liquidity and stock's trading characteristics

To formally test the liquidity differences across the three sub-period: pre-crisis, crisis, and post-Arrowhead, I analyze the following regression (Stoll, 2000):

$$\boldsymbol{COI\ or\ LOB\ SLOPE} = \propto_0 + \boldsymbol{\beta_1 ARROWHEAD + \beta_2 CRISIS + \beta_3 LogVOL + \beta_4 LogNTRD +}$$

$$\boldsymbol{\beta_5 LogMV + \beta_6 LogPRICE + \beta_7 PRIVAR + \varepsilon}$$

where *COI* (=*ASKCOI*+ *BIDCOI*) measures the cost that liquidity demanders have to bear above the intrinsic value due to a sudden surge in the demand for 1% of the daily average trading volume. LOB Slope for the five best asks (*ASKSLOPE*) and five best bids (*BIDSLOPE*) is calculated using Equations 4 and 5, respectively. *SLOPE* is (*BIDSLOPE* + *ASKSLOPE*)/2. *ARROWHEAD* is a dummy variable that takes a value of 1 for the post-Arrowhead period of January 2011, zero, otherwise, *CRISIS* is a dummy variable that takes a value of 1 for the crisis period of January 2009, zero, otherwise, *VOL* is the volume traded, and *NTRDS* is the number of trades for every minute of trading. *MV* is the stock's market value, *PRICE* is the stock's price at the end of every 5 minute period, *PRIVAR* is the price volatility for every minute of trading, and $\boldsymbol{\varepsilon}$ is the error term. Statistical inference is conducted using Thompson (2009) standard errors

Dependent Variable	**COI**		**LOB SLOPE**	
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
INTERCEPT	0.03**	0.03**	0.02**	0.04**
ARROWHEAD	-0.06**	-0.05**	0.10**	0.09**
CRISIS	0.03**	0.03**	0.01	0.01
LOG VOL		-0.03**		0.04**
LOG NTRDS		-0.04**		0.02**
LOG MV		-0.04**		0.03**
LOG PRICE		-0.03*		0.03*
PRIVAR		0.04**		-0.06**
ADJ R^2	0.01	0.22	0.02	0.28

** Significant at 5% level
* Significant at 10% level

Table 4.

Volatility

I report the results from the following GARCH specification:

$$R_t = \sum_{k=1}^{5} \propto_k D_k + \sum_{j=1}^{12} \beta_j R_{t-j} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \beta_1 ARROWHEAD_{\mathrm{t}} + \beta_2 CRISIS_{\mathrm{t}} + \beta_3 RSPRD_{\mathrm{t}} + \beta_4 DEPTH_{\mathrm{t}} + \beta_5 VOL_{\mathrm{t}} + \beta_6 NTRD_{\mathrm{t}} + \beta_7 M_{\mathrm{t}} + \alpha_1 \varepsilon_{\mathrm{t}-1}^2 + \gamma \sigma_{t-1}^2$$

R_t is the return on a stock for the one minute interval *t*, D_k is a day-of-the-week dummy for day *k*, σ_t^2 is the conditional variance of ε_t from the return equation, *ARROWHEAD* is a dummy variable that takes a value of 1 for the post-Arrowhead period of January 2011, zero, otherwise, *CRISIS* is a dummy variable that takes a value of 1 for the crisis period of January 2009, zero, otherwise, *RSPRD* is the time relative spread, *DEPTH* is the average volume supplied at the best bid and best ask, *ATS* is the average trade size, *VOL* is the volume traded, *NTRD* is the number of trades for each minute of trading, *M* is a dummy variable that is equal to 1 for Mondays and 0 otherwise, and ε_t is the residual from the return equation. I report the standardized parameter estimates in this table.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
ARROWHEAD	-2.16**		-1.66**	-1.42**
CRISIS		0.95**	1.21**	0.73**
RSPRD				0.09*
DEPTH				0.01
VOL				0.01
NTRDS				0.65**
MONDAY				0.03
ADJ. R^2	0.11	0.04	0.15	0.22

** Significant at 5% level
* Significant at 10% level

Table 5.

REITs vs non-REITs: Difference-in-Differences analysis

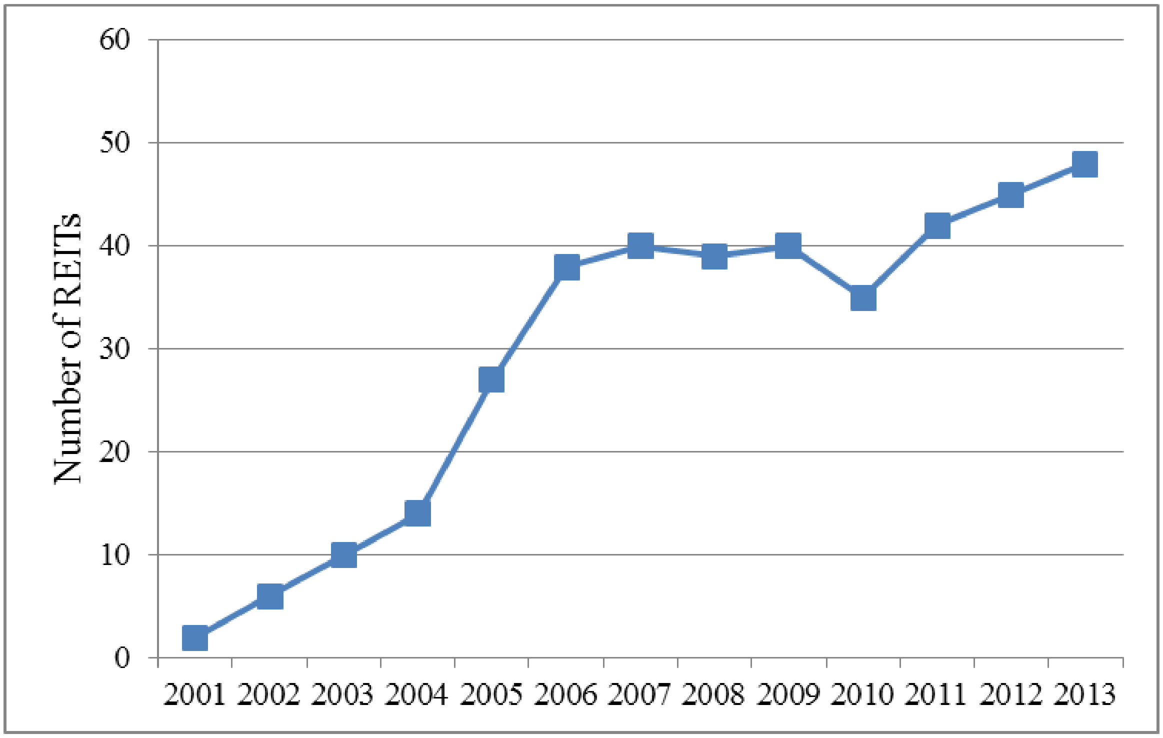
To formally test whether REITs have lower information asymmetry and easier and efficient price discovery as compared to non-REIT common stocks, following difference-in-differences regression model is analyzed:

$$\boldsymbol{Y} = \propto_{\mathbf{0}} + \mu + \boldsymbol{\beta_1 ARROW} + \boldsymbol{\beta_2 CRISIS} + \boldsymbol{\beta_3 ARROW} * \boldsymbol{REIT} + \boldsymbol{\beta_4 CRISIS} * \boldsymbol{REIT} + \boldsymbol{\beta_5 X} + \boldsymbol{\varepsilon}$$

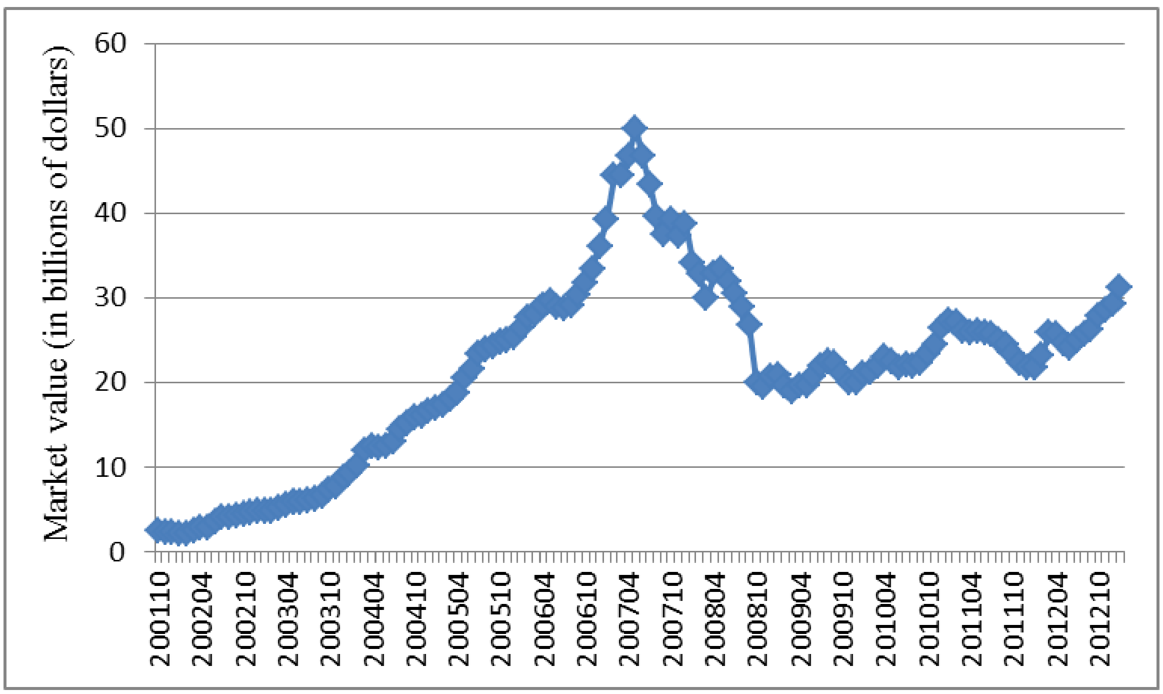
where *Y* is the market quality variable of interest (e.g., *SLOPE*, *COI*, or *VOLATILITY*), μ is the firm-specific effect, *ARROW* is an indicator variable that takes a value of 1 for the post-Arrowhead period, zero otherwise, *CRISIS* is a dummy variable that takes a value of 1 for the crisis period, zero otherwise, *REIT* is an indicator variable that takes a value of 1 for REIT common stock and zero for a market capitalization matched non-REIT common stock, and X is a set of control variables used in the previous analyses (including a *REIT* dummy variable is unnecessary in this framework specifically because we include firm fixed effects). Statistical inference is conducted using White's standard errors.

Variables	**COI**	**LOB SLOPE**	**VOLATILITY**
INTERCEPT	0.07**	0.05**	0.02**
ARROW*REIT	0.08**	-0.07**	0.19**
CRISIS*REIT	-0.12**	0.13**	-0.21**
ARROW	-0.14**	0.16**	-1.78**
CRISIS	0.18**	-0.12**	1.03**
LOG VOL	-0.03*	0.05**	0.08**
LOG NTRDS	-0.10**	0.01	0.15**
LOG MV	-0.11**	0.07**	
LOG PRICE	-0.02	0.03*	
PRIVAR	0.04*	-0.08**	
RSPRD			0.05*
DEPTH			0.03
MONDAY			0.01
Firm fixed effects	Yes	Yes	Yes
ADJ R^2	0.31	0.38	0.25

** Significant at 5% level
* Significant at 10% level

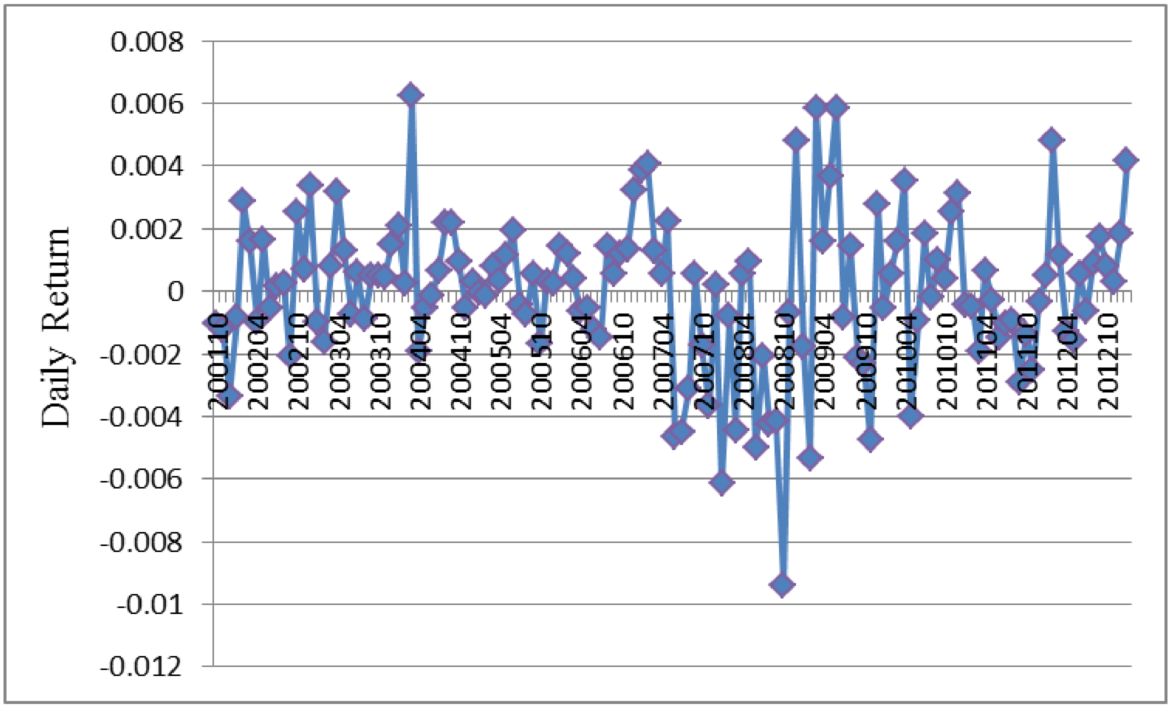


Panel A. Change in the number of listed J-REITs since their inception

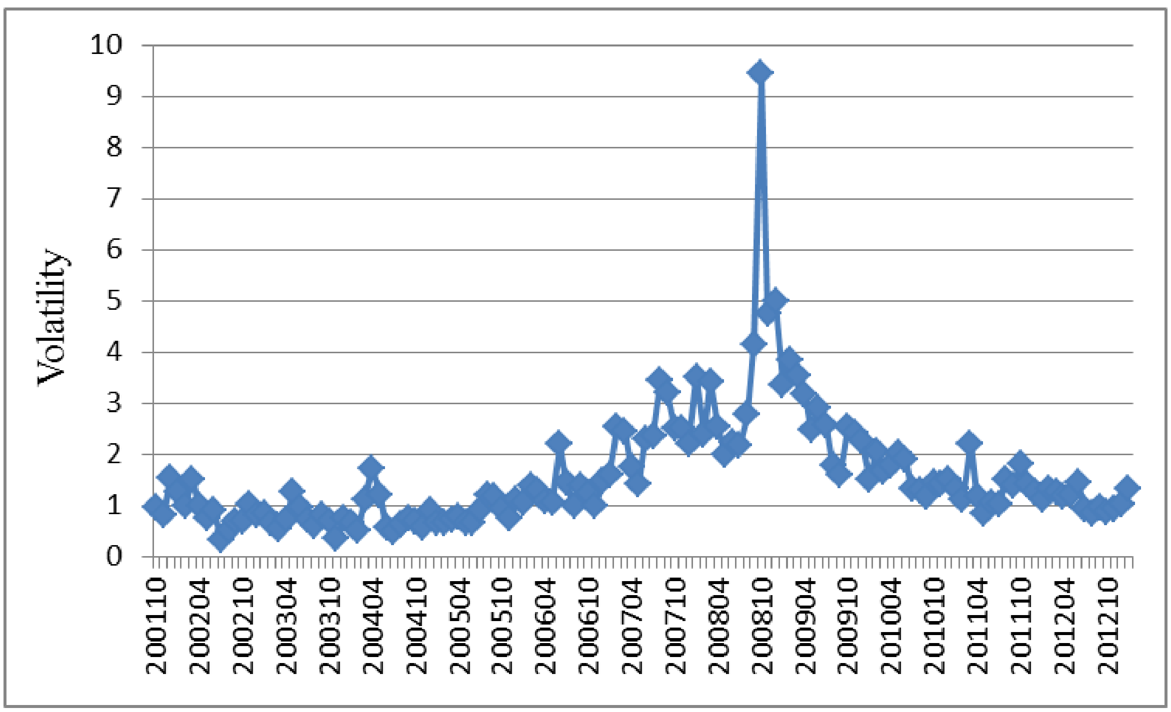


Panel B. Change in the market value of listed J-REITs since their inception

Figure 1. Evolution of J-REIT market

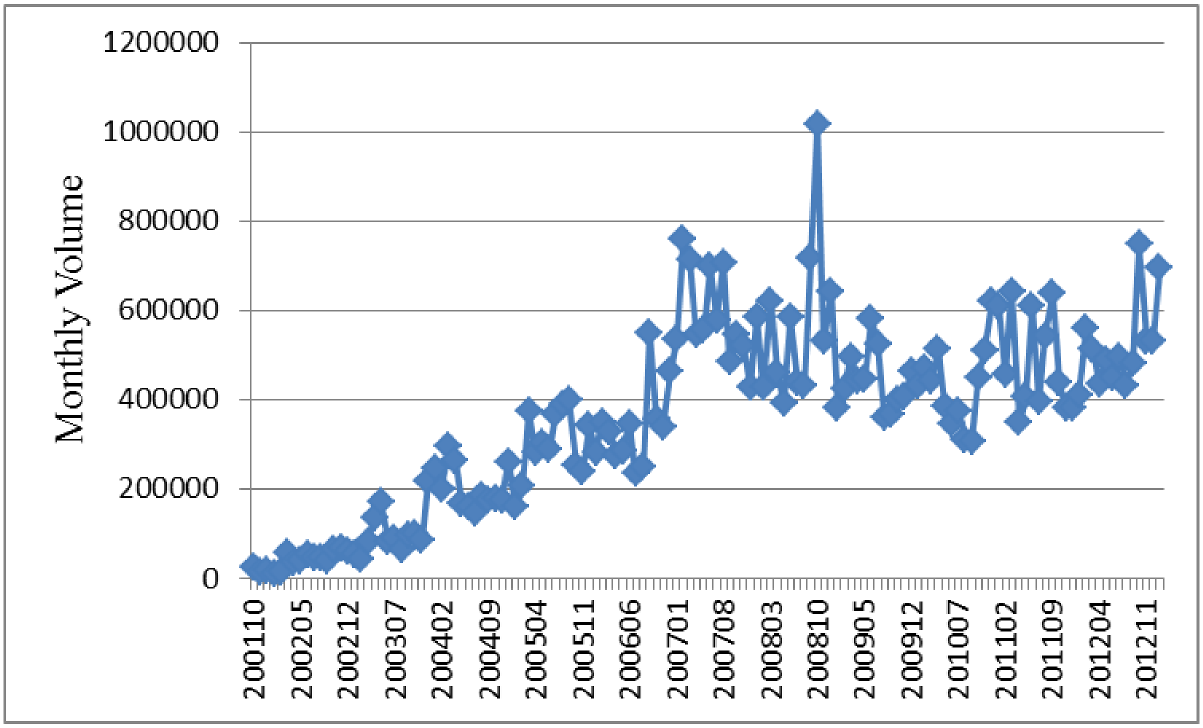


Panel A. Daily return for listed J-REITs based on closing prices

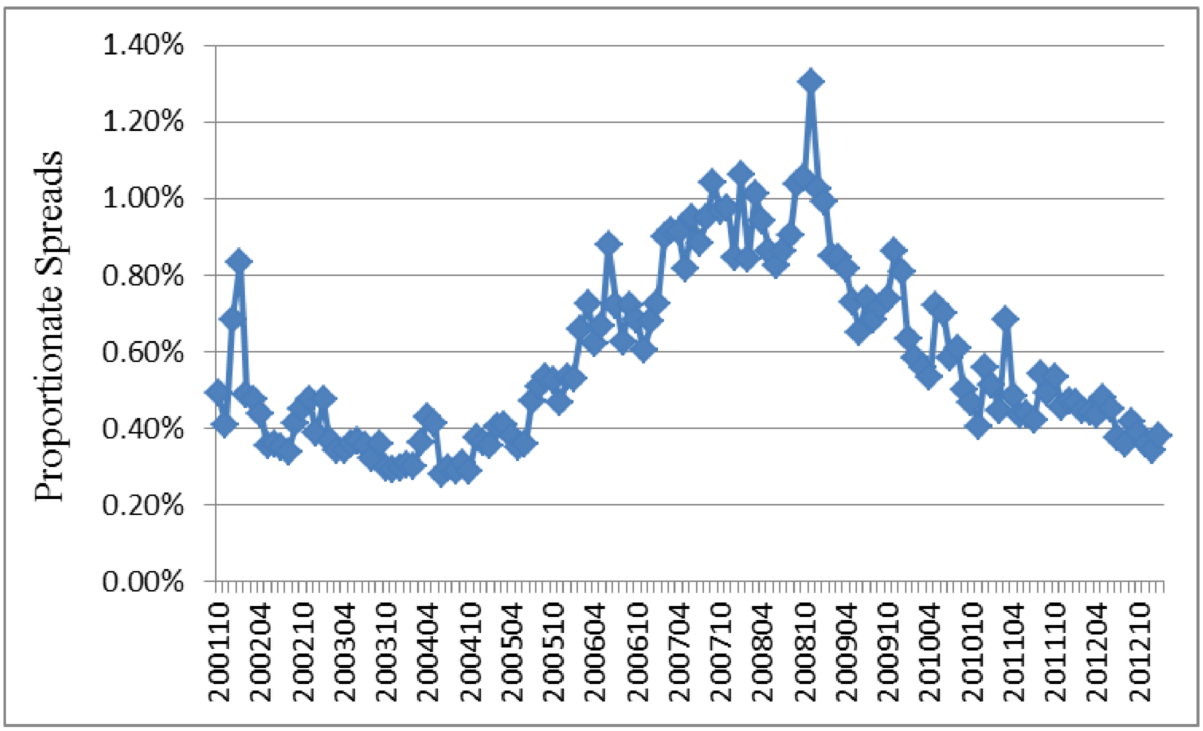


Panel B. Daily returns volatility for listed J-REITs computed as the standard deviation of returns

Figure 2. Daily return and return volatility for the listed J-REITs



Panel A. Monthly volume for listed J-REITs since inception



Panel B. Daily proportionate spreads for listed J-REITs since inception

Figure 3. Monthly volume and proportionate spreads for the listed J-REITs

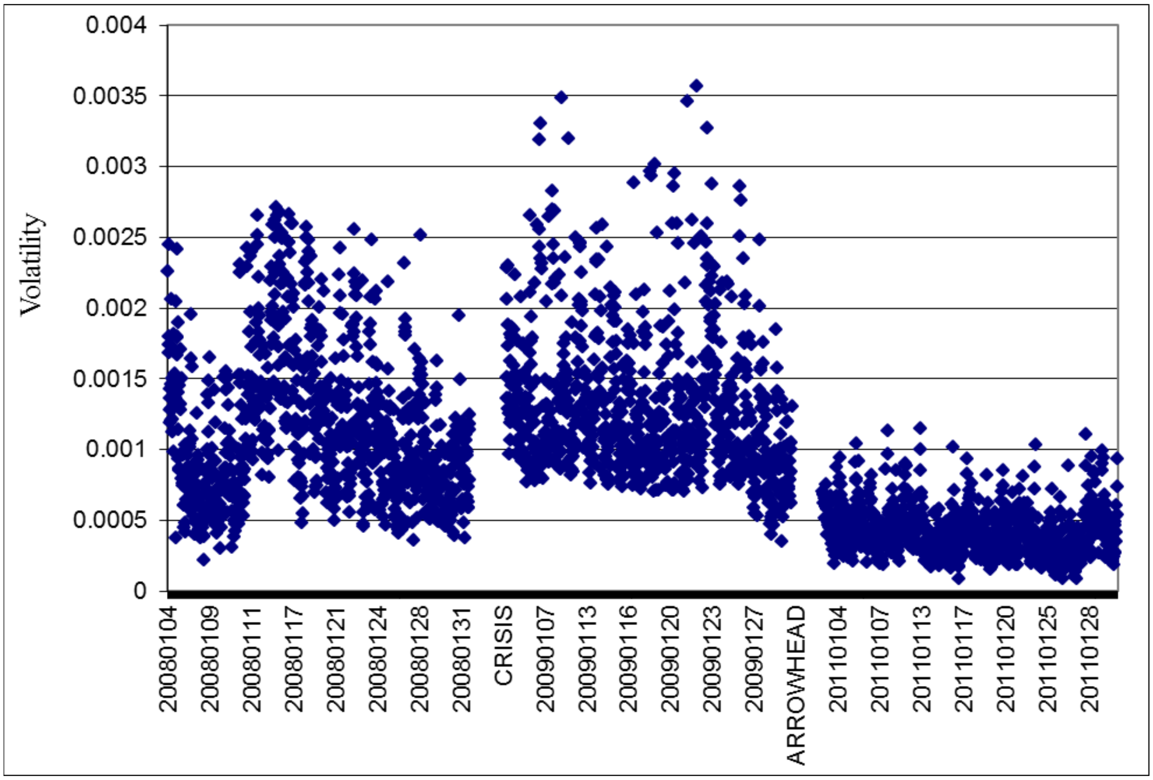


Figure 4: Evolution of volatility during the crisis and post-Arrowhead period

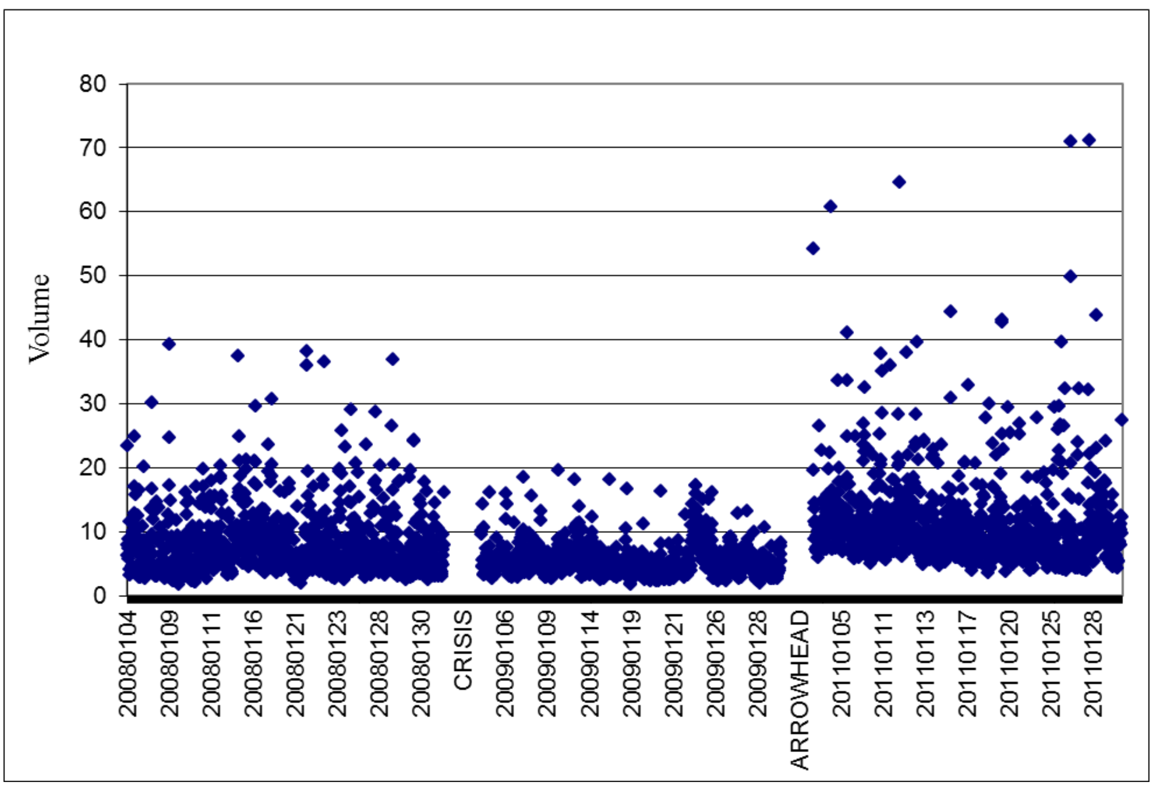


Figure 5: Evolution of volume during the crisis and post-Arrowhead period

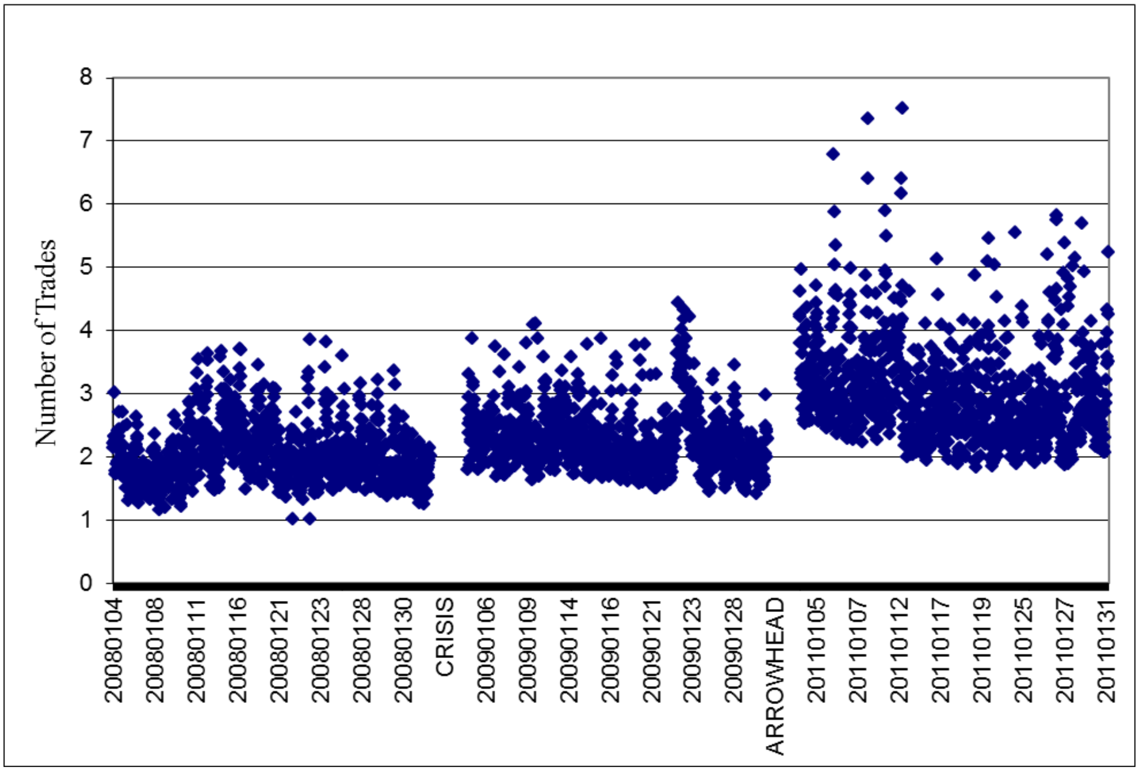


Figure 6: Evolution of number of trades during the crisis and post-Arrowhead period

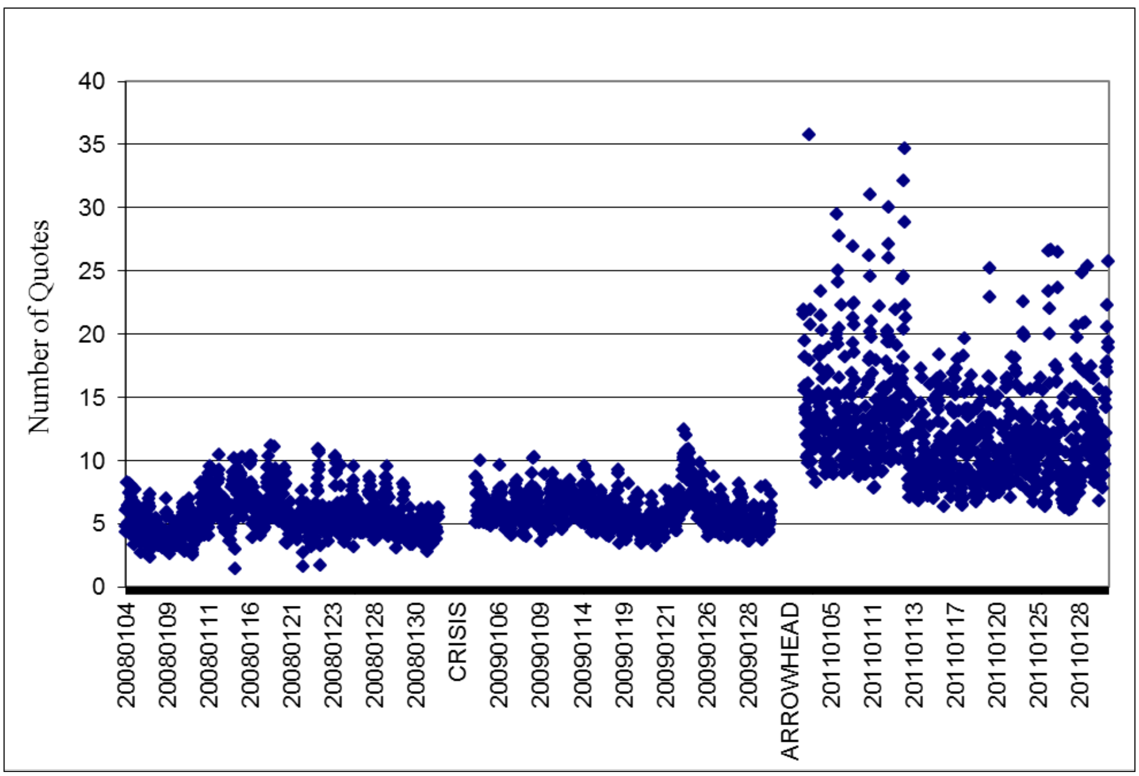


Figure 7: Evolution of number of quotes during the crisis and post-Arrowhead period

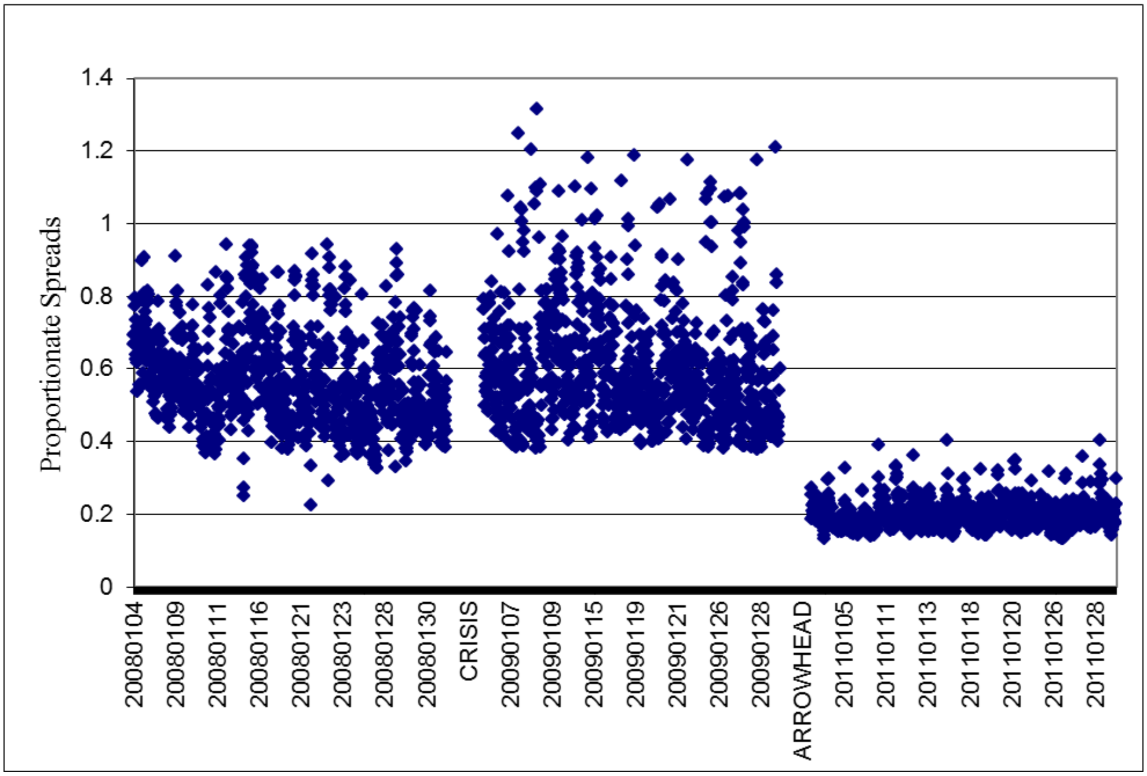


Figure 8: Evolution of proportionate spreads during the crisis and post-Arrowhead period

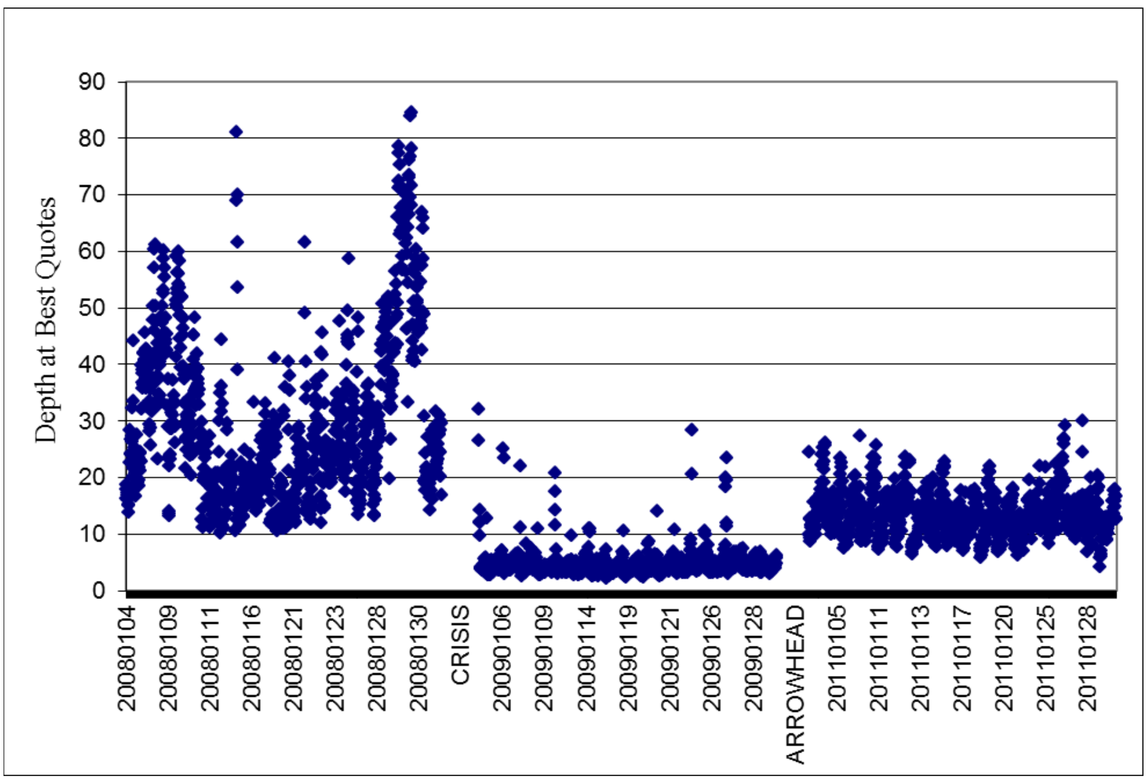


Figure 9: Evolution of depth during the crisis and post-Arrowhead period

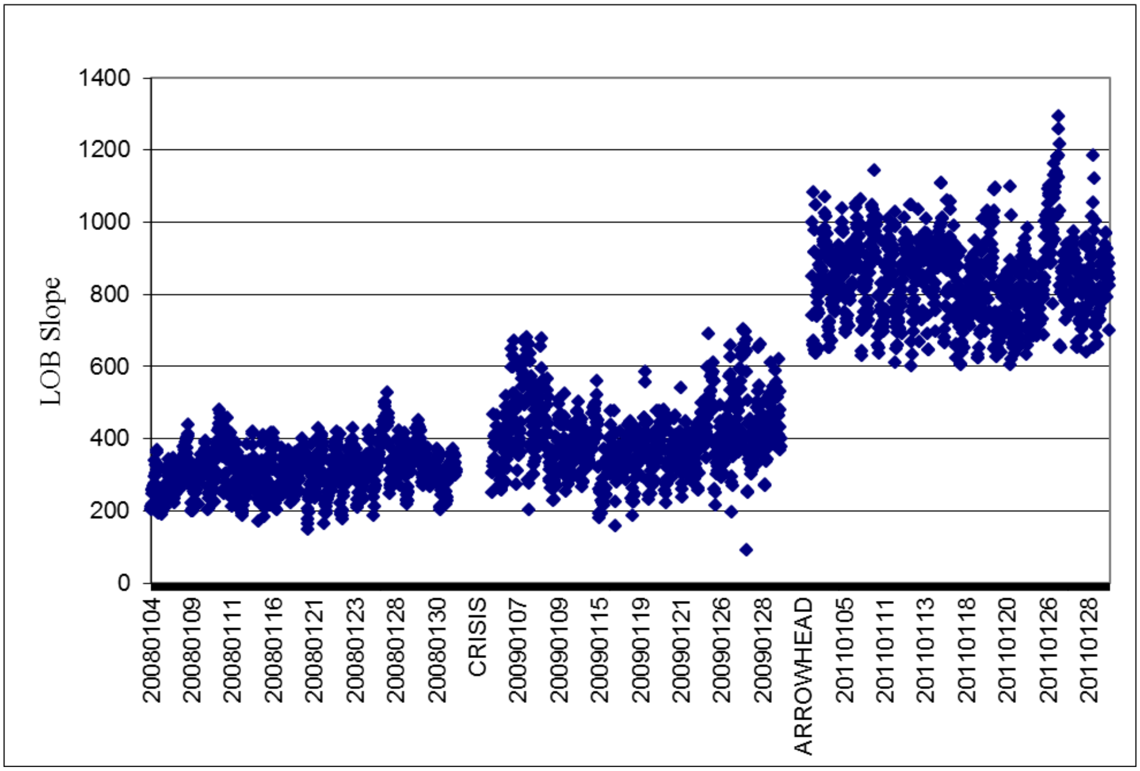


Figure 10: Evolution of LOB Slope during the crisis and post-Arrowhead period

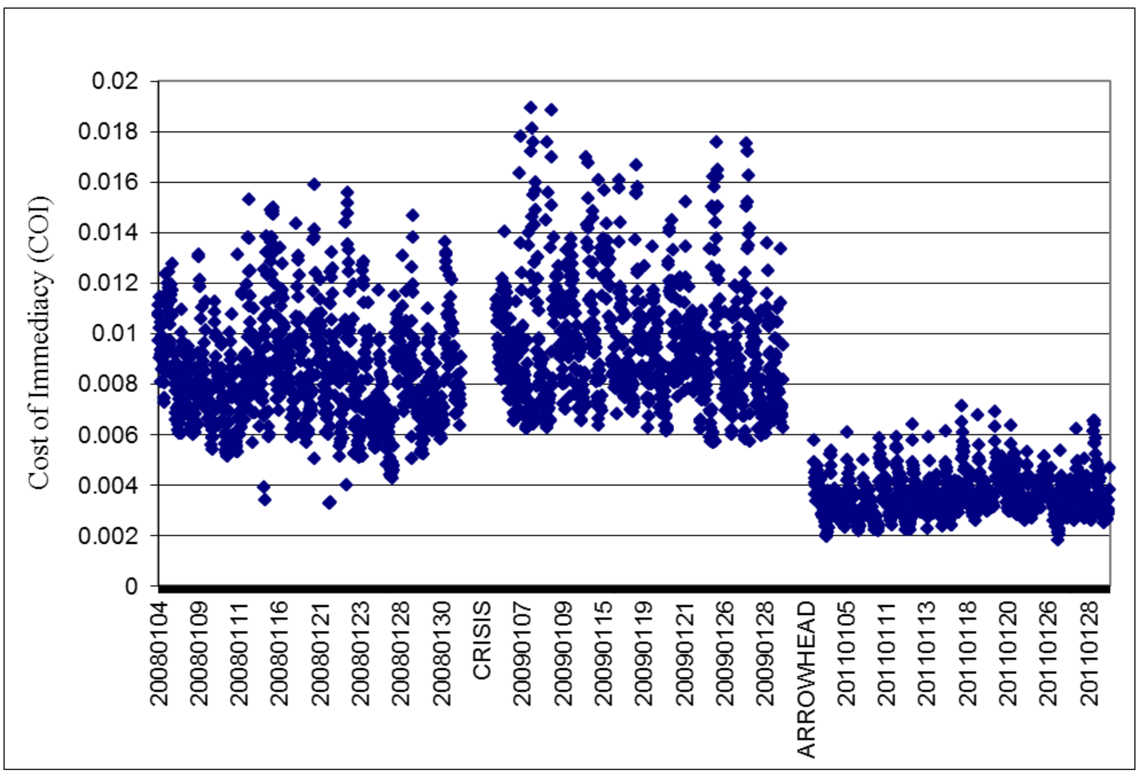


Figure 11: Evolution of cost-of-immediacy during the crisis and post-Arrowhead period

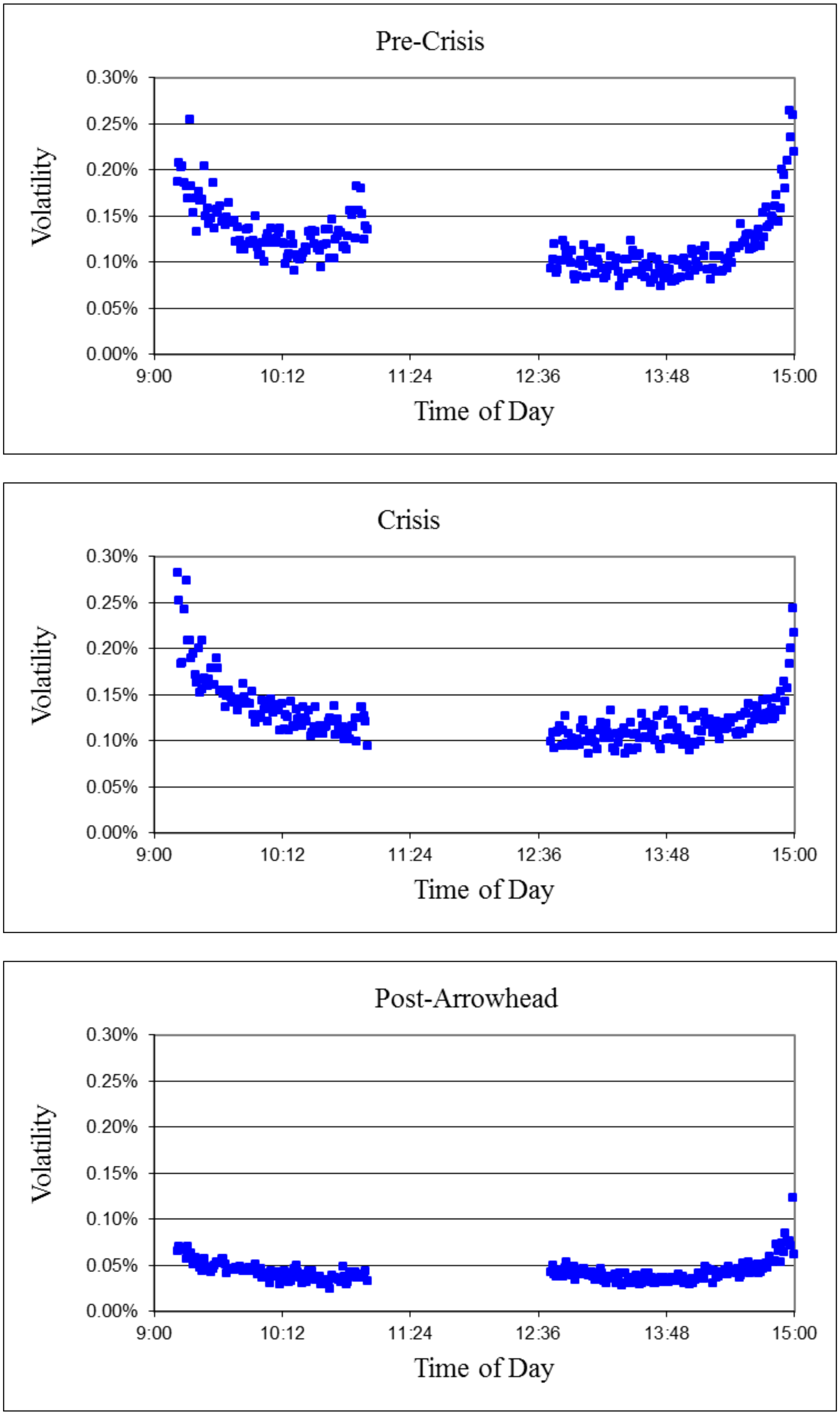


Figure 12: Intraday patterns for minute-by-minute volatility

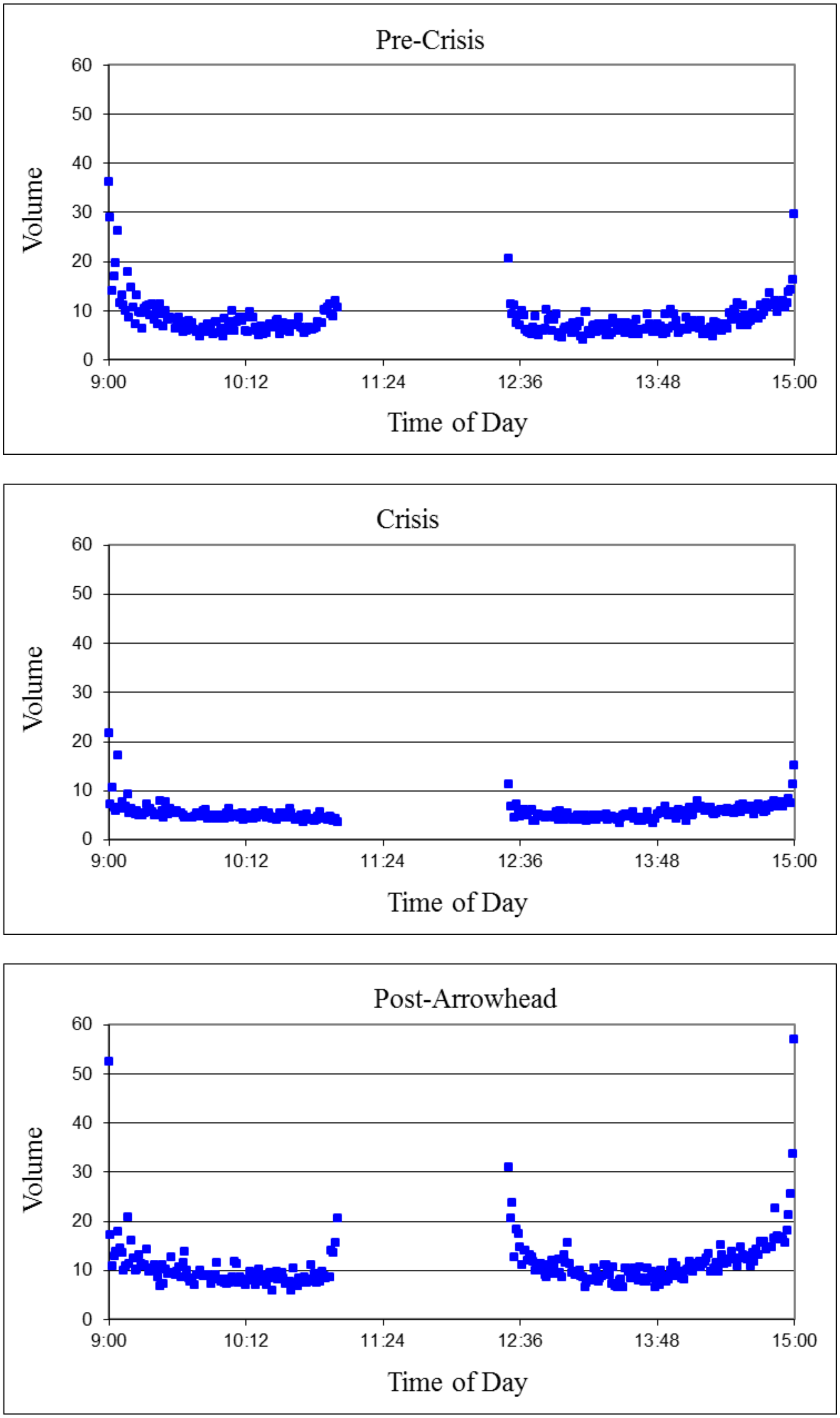


Figure 13: Intraday patterns for minute-by-minute trading volume

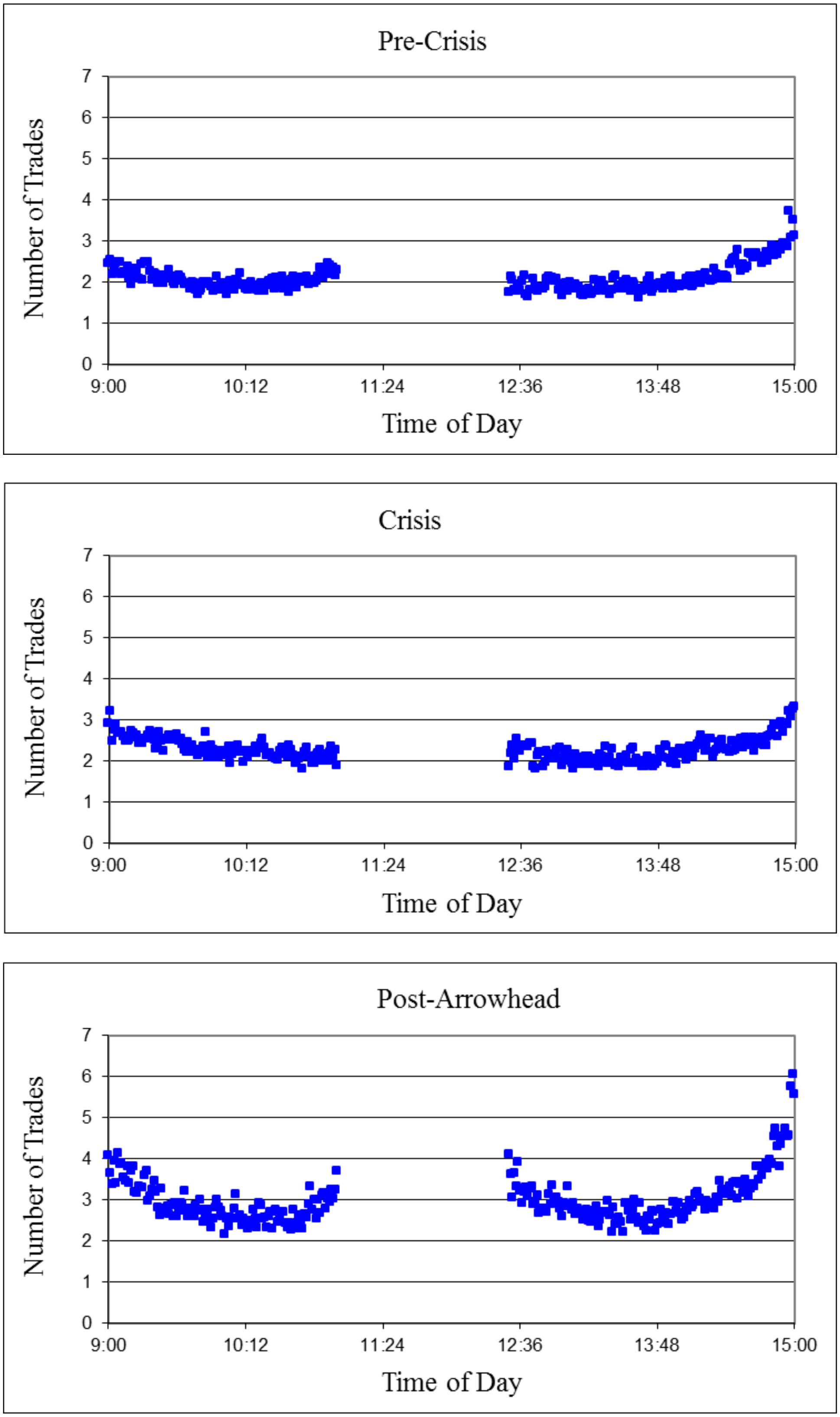


Figure 14: Intraday patterns for minute-by-minute number of trades

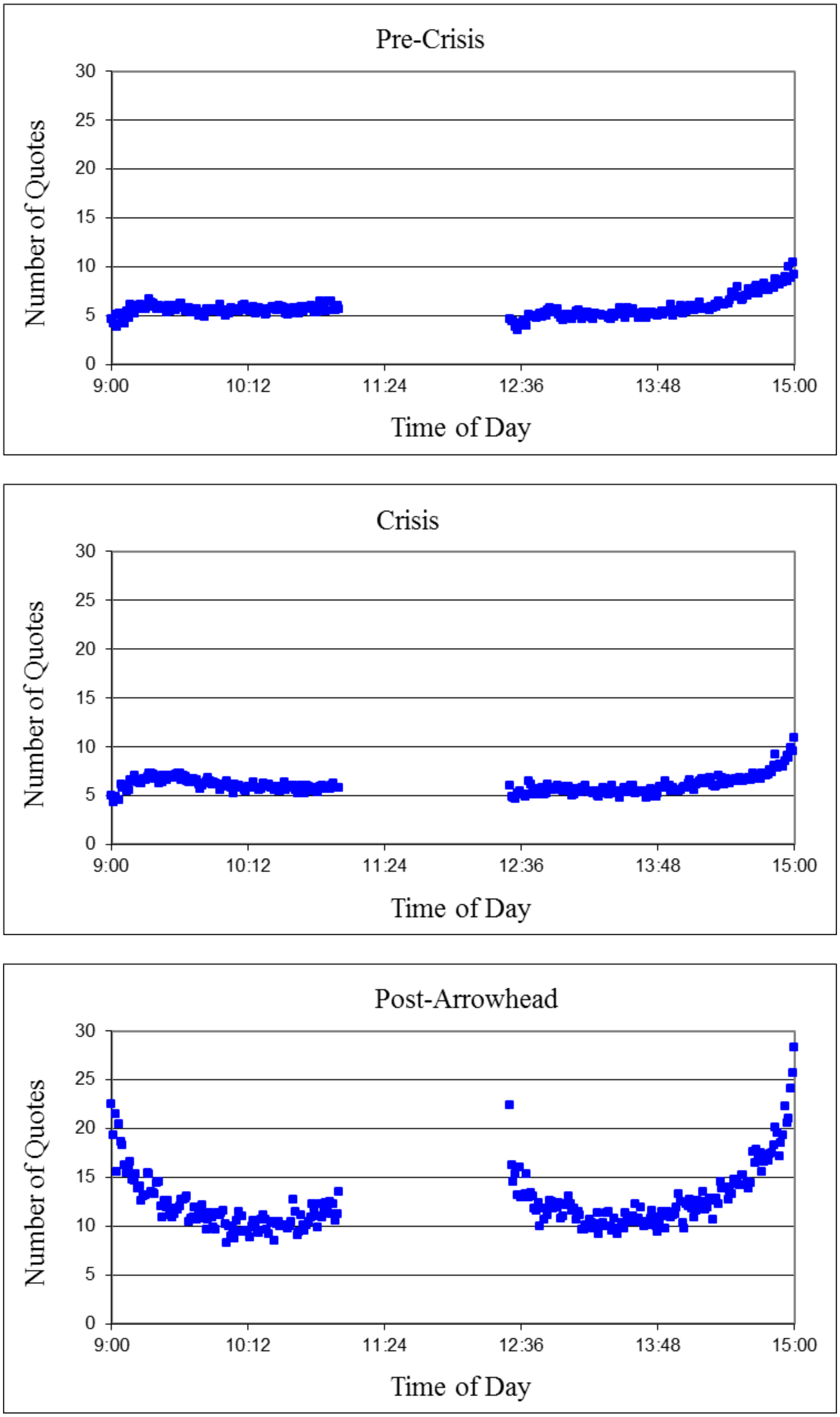


Figure 15: Intraday patterns for minute-by-minute number of quotes

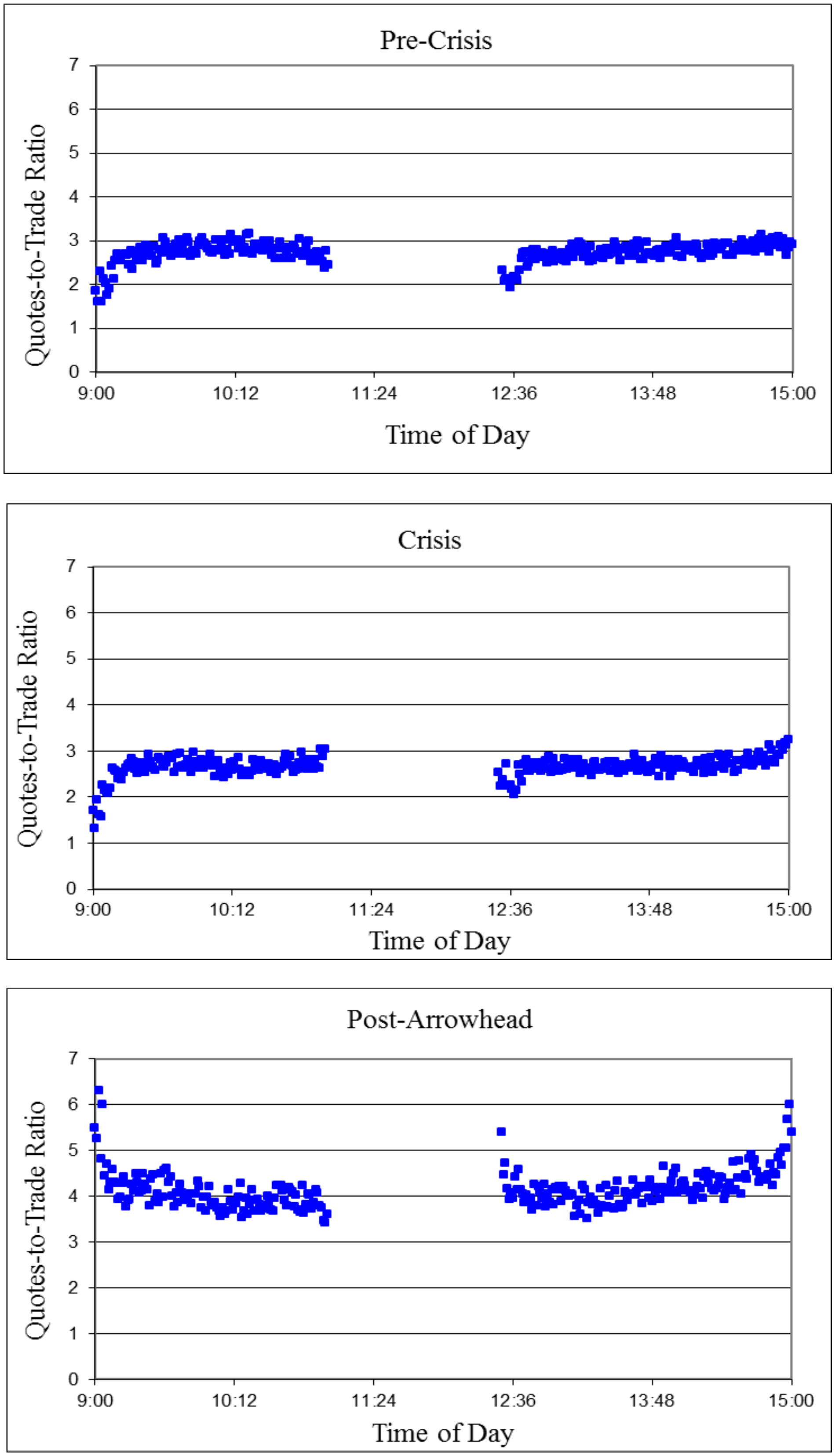
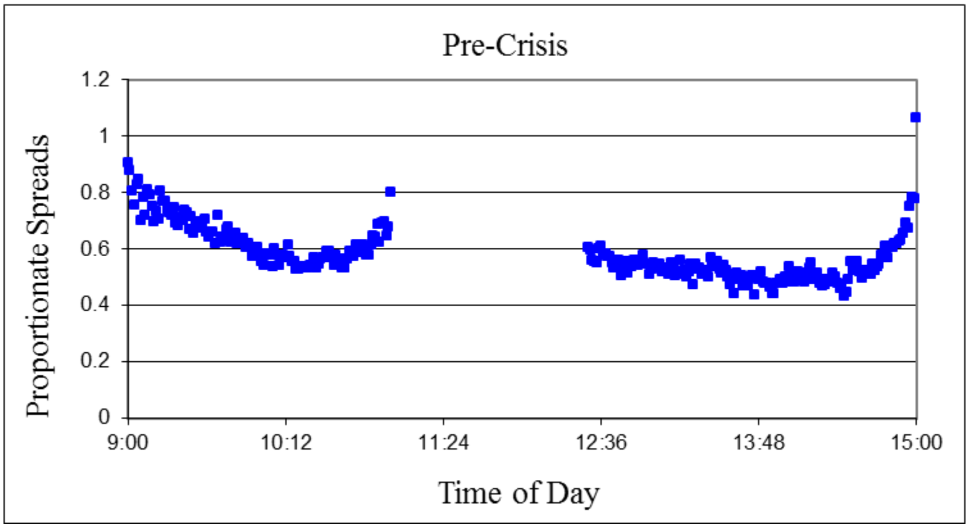
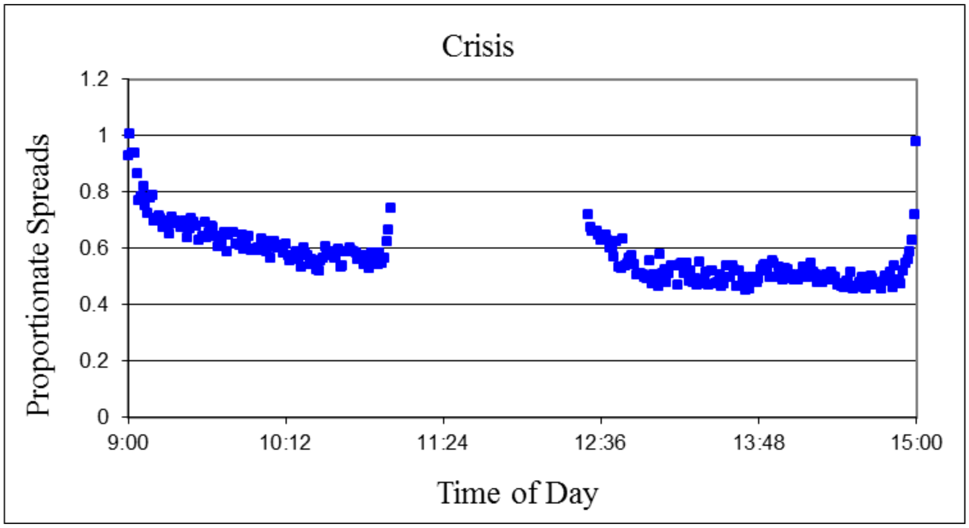


Figure 16: Intraday patterns for minute-by-minute quotes-to-trade ratio





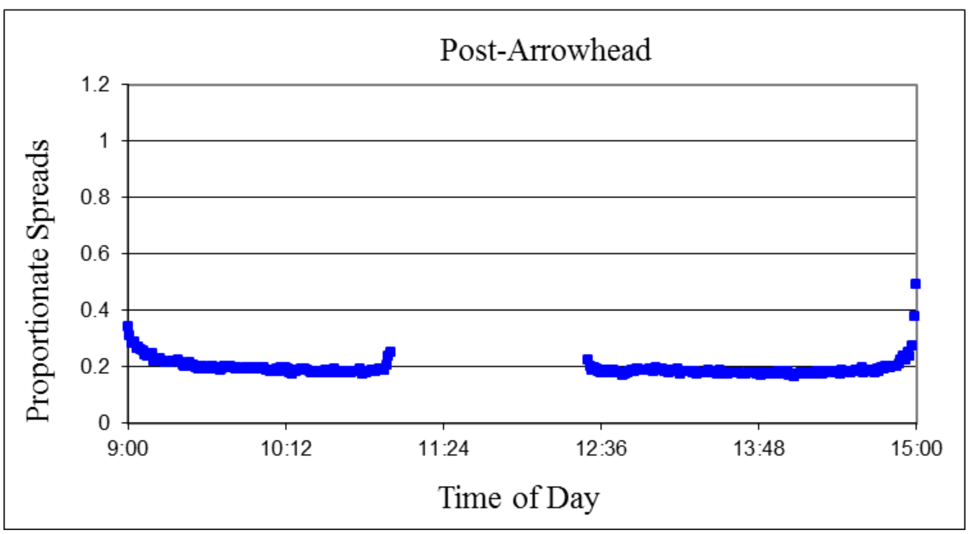


Figure 17: Intraday patterns for minute-by-minute proportionate spreads

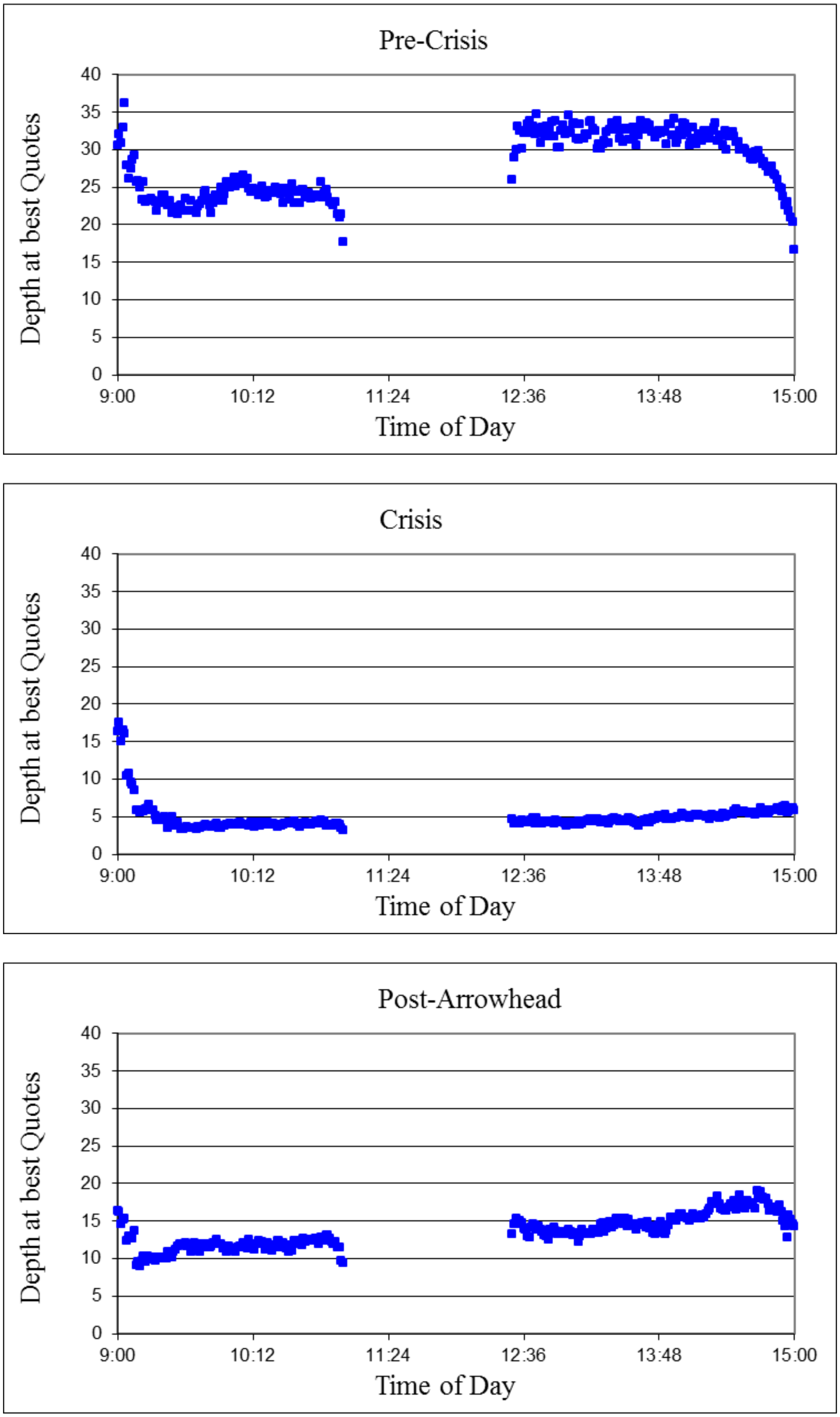


Figure 18: Intraday patterns for minute-by-minute top of the book depth

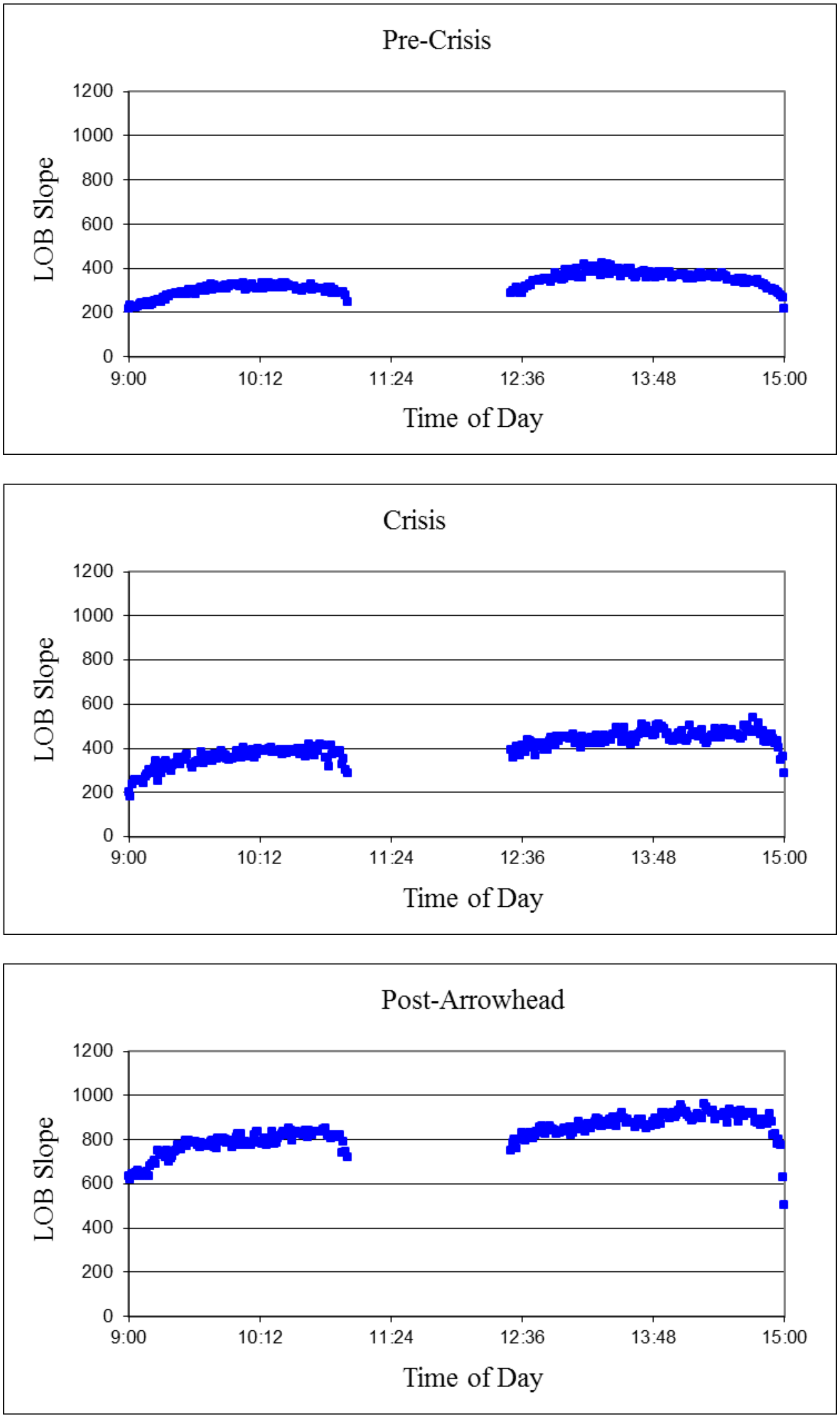


Figure 19: Intraday patterns for minute-by-minute LOB Slope

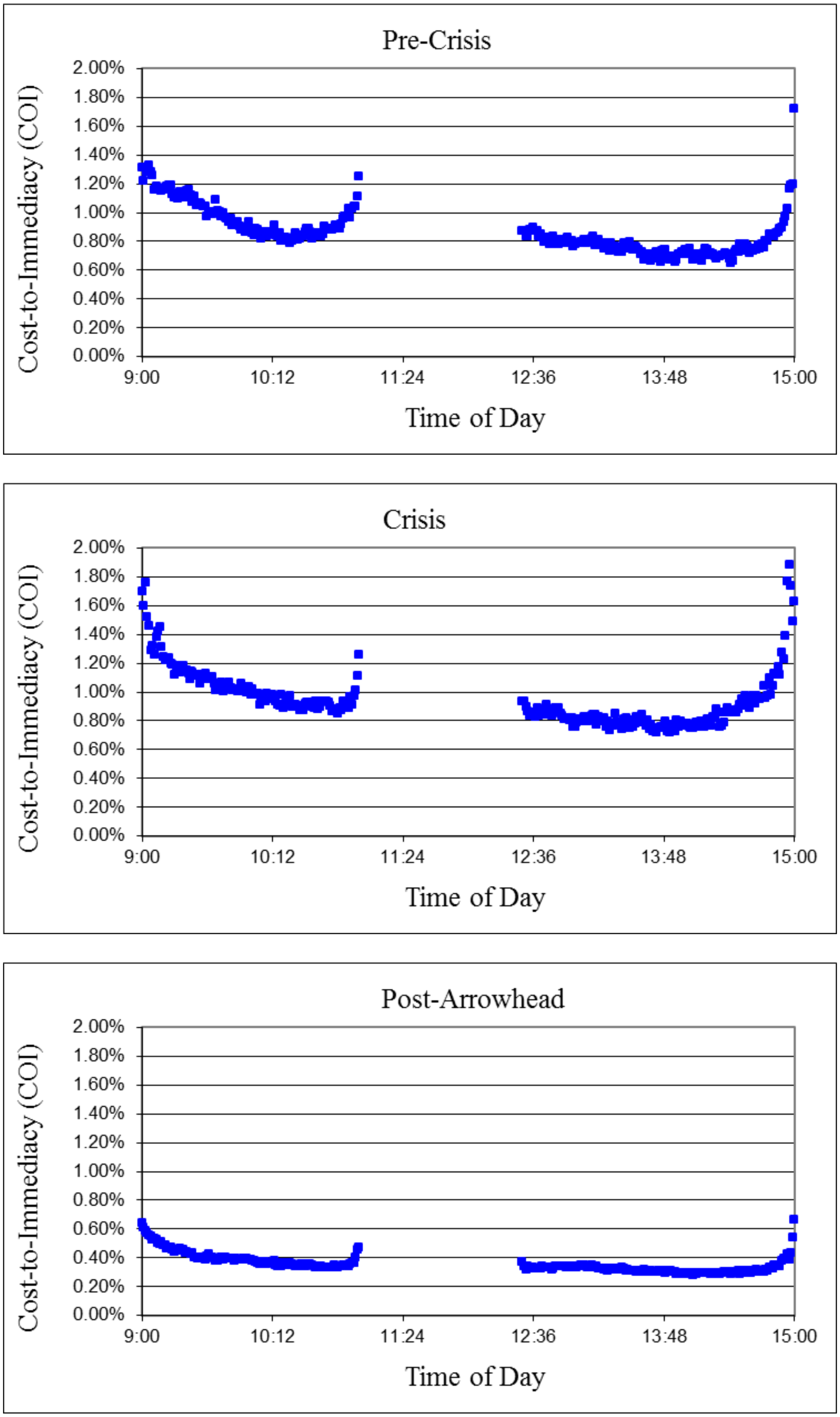


Figure 20: Intraday patterns for minute-by-minute cost-of-immediacy (COI)