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Implication of Mandatory Trading Report: Evidence from the Thai Bond Market

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Abstract

Motivated by mixed evidence on market transparency and two regulatory changes introduced by the Thai Bond Market Association (ThaiBMA) in 2006 and 2009, this study examines their effects on bond liquidity and extreme price jumps. The 2006 regulation required the reporting of trading information within 30 minutes, and the 2009 regulation imposed penalties for late, erroneous, or missing reports. Using 745,911 Thai government bond transactions from 2002 to 2019, we find that mandatory reporting reduced average reporting delays by about 49–59 seconds, while the introduction of penalties reinforced compliance. Liquidity improved, with the 2006 regulation linked to a 46 basis point increase in turnover, although effects after 2009 were less pronounced. Most strikingly, the frequency of extreme price jumps declined sharply: only one weekly jump was detected across four actively traded bonds after 2006, compared with frequent jumps beforehand. These results demonstrate that even modest improvements in reporting timeliness can enhance transparency, strengthen investor confidence, and reduce tail-risk exposure. Overall, regulatory enforcement contributed to more stable market conditions and may lower the cost of capital in emerging bond markets.

Keywords: Market Transparency; Post-Trade Reporting; Market Liquidity; Regulatory Disclosure; Thai Bond Market

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Introduction

In recent years, researchers have increasingly focused on improving bond market transparency. A survey of European capital markets revealed that nearly all participants were in favor of greater transparency in post-trade transactions[1]. Those surveyed believed that the transparency requirements of MiFID II[2] would benefit the European fixed income markets. The survey results also indicated that enhanced transparency under MiFID II would have a considerable impact on fixed income market liquidity.

Market transparency refers to the information available to participants about the trading process. It includes pre-trade transparency, which provides details on trade inputs to help investors secure favourable prices, and post-trade transparency, which discloses completed transactions, enabling investors to assess execution quality. This framework follows O'Hara (1995). When appropriately delayed, post-trade transparency may offer insights into actual market activity. Numerous studies have examined its impact on liquidity, using proxies such as price dispersion and trading volume. Most regulators believe that greater transparency enhances market liquidity, improves pricing efficiency, and encourages broader investor participation.

Generally, trading cost is often used as a measure to assess the impact of increased transparency on market liquidity. When a market is more transparent, liquidity providers can offer lower trading costs, which are typically measured by the effective bid-offer spread, to uninformed traders. Additionally, enhancing transparency can decrease the price that market makers charge for exchanging securities (Pagano & Roell, 1996). Further, Naik et al. (1999) argue that increased transparency can lower dealers' holding costs, which in turn can reduce trading costs in a dealer market. Such transparency can also encourage more traders to participate, giving them an advantage over dealers and ultimately reducing trading costs (Chen & Zhong, 2012). Theoretical studies suggest that spreads decline in transparent markets (Edwards et al., 2007; Goldstein et al., 2007). Relatedly, Duffie et al. (2009) documents the post-trade transparency, liquidity provision and dealer incentives, which further motivates our empirical investigation. Additionally, increased transparency also leads to improvement in market efficiency with lower volatility, less frequent jumps and fewer informed traders. However, empirical findings indicate that the impact of enhanced transparency and efficiency is contingent upon the market structure and the securities traded.

Regulations regarding transparency differ across countries worldwide. As an illustration, in Europe, the Markets in Financial Instruments Directive II (MiFID II) mandates that trades in government bonds must be disclosed within 15 minutes and with certain limits. In the initial years of the Trade Reporting and Compliance Engine (TRACE), another regulatory change resulted in a shorter reporting window for dealers. This change led to a decrease in execution costs for large insurance companies that utilized TRACE for transaction reporting. In general, an increase in transparency tends to improve market liquidity and eventually market efficiency. The ThaiBMA introduced two related regulations regarding post-

[1] A survey in the annual MarketAxess and Trax European Capital Markets Forum, Andaz Hotel, Liverpool Street, London, on Thursday, 11 May 2017.
[2] Financial Instruments Directive (MiFID II) reporting requirements aim to boost investor protection by strengthening the transparency framework for the regulation of markets in financial instruments, including OTC markets. Under MiFID II, post-trade data must publish as close to real time as is technically possible (15 min. limit).

trade transparency for Thailand in 2006 and 2009. This motivates us to evaluate the effectiveness of such regulations on market transparency and efficiency.

We contribute to the literature by focusing on the emerging bond market, with Thailand being one of the fastest growing financial hubs in the Southeast Asian region. By imposing reporting standards, the market information is more transparent, leading to greater degree of investor confidence. Given the significance of this issue, we analyse the trading prices of the Thai Government Bonds over the period of 2002 to 2019. We found notable patterns in trading delays, liquidity fluctuations, and bond price jumps, with 85% of total transactions reported within 30 minutes, adhering to regulatory requirements. Liquidity and jump measures indicate improved market transparency after the imposition of the reporting regulations. These findings highlight the significance of timely reporting and regulatory oversight in maintaining market stability and efficiency.

The remainder of this paper is structured as followed. Section 2 provides the review of the related literature. The description of the data and methodology used in this study is covered in Section 3. Section 4 discusses the empirical findings, and Section 5 concludes.

Literature Review

Background on Thai Bond Market Regulation

Bond trading in Thailand operates on an Over the Counter (OTC) basis, primarily conducted through telephone negotiations or voice brokers. Dealers, who are SEC-licensed financial institutions, must report all bond transactions to ThaiBMA within a specified timeframe. The prices disseminated by ThaiBMA serve as crucial market references for mark-to-market (MTM) valuations, ensuring transparency and efficiency in the Thai bond market.

The Notification of the Thai Bond Market Association Re: Terms, Conditions, and Procedure concerning Reporting of Debt Instrument Trading requires dealers to report transaction information and governs post-trade deferred publication. This regulation came into effect in January 2006. Under it, dealers must report all required trading information to ThaiBMA within 30 minutes of execution for public dissemination. In 2009, another regulation was imposed. The Notification of the Board of Directors of the Thai Bond Market Association Re: Administrative Sanctions concerning Reporting of Debt Instrument Trading[3] is the penalty for late transaction, error transaction, or missing transaction.

Unlike stock markets, the bond market operates over-the-counter (OTC), with transactions conducted through dealers. A trade may occur between dealers (e.g., dealer A sells to dealer B), or between a dealer and an investor (e.g., dealer A sells to investor C). Investors include banks, mutual funds, insurance companies, and corporations. Under current regulations, all dealers must report their transactions to ThaiBMA. Transactions between two dealers must be reported separately by both parties, whereas transactions with investors are reported only once by the dealer.

[3] See Thai Bond Market Association (2014). Announcement No. 40/2014: Authority of the Board of Directors under Clause 20(2) and Clause 68 of the Articles of Association (in Thai). Retrieved from http://www.thaibma.or.th/pdf/sro/announce/announce40_jan2014.pdf

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In addition, ThaiBMA regulations require that transactions executed before 15:30 be reported on the same day, while those after 15:30 must be reported by 9:30 on the following business day. Dealers who fail to comply or who submit uncorrected, missing, or erroneous transaction reports are subject to fines of varying amounts.

Members may get disciplinary actions as follows[4];
1) Warning;
2) Probation;
3) Fine (The maximum level of the fine in each case shall not exceed 300,000 THB.)

Besides the fine penalty, if dealers are found to have intention not to report according to the terms, conditions, and procedure concerning reporting of Debt Instrument Trading (the notification in 2008), a disciplinary committee shall apply the penalty with the other disciplinary procedures. Dealer members will be barred from any member rights and terminated from membership.

The effect of transparency on market liquidity

The relationship between transparency and market liquidity is complex and context-dependent, influenced by market structure and the specific type of transparency. Transparency can enhance liquidity by reducing bid-ask spreads, information asymmetry, and price impact, while increasing market depth and trading volume. However, excessive transparency may overwhelm participants, impair decision-making, and cause instability. Accordingly, existing studies offer mixed evidence of both positive and negative effects.

Studies showing a positive link include Pagano and Roell (1996), Flood et al. (1999), Chen and Zhong (2012), Bessembinder et al. (2006), Edwards et al. (2007), and Goldstein et al. (2007). For instance, Pagano and Roell (1996) find that transparency improves liquidity and reduces market-making costs by narrowing spreads. Similarly, Flood et al. (1999) show that pre-trade transparency lowers bid-ask spreads. Building on Hong and Warga (2000) and Chakravarty and Sarkar (2003), Chen and Zhong (2012) estimate the effective spreads of transparent bonds and find that pre-trade transparency enhances liquidity and attracts more traders.

Conversely, studies such as Bloomfield and O'Hara (1999), Porter and Weaver (1998), Balakrishnan et al. (2014), Dang et al. (2015) and Holmstrom (2015) report adverse effects. Bloomfield and O'Hara (1999) observe wider opening bid-ask spreads with greater transparency. Porter and Weaver (1998), using Toronto Stock Exchange data, find spreads widen when deeper levels of bid-offer information are disclosed. They conclude that increased transparency may reduce liquidity. Holmstrom (2015), Dang et al. (2015), and Balakrishnan et al. (2014) argue that disclosing complex debt market information can hinder trading rather than facilitate it.

Measuring market liquidity is a critical aspect of financial analysis and risk management. Liquidity refers to the ease with which an asset can be traded without significantly affecting its price. Accurate liquidity measurement is essential for investors, traders, policymakers, and financial institutions, offering insights into market behavior, risk, and investment decisions. Importantly, liquidity measurement is not uniform; different asset classes—equities, bonds, currencies, and commodities—require tailored metrics. Liquidity

[4] See Securities and Exchange Act, B.E. 2535 (A.D. 1992), Consolidated Version as of 2012. Retrieved from http://www.thaibma.or.th/pdf/sro/announce/Codified2555.pdf

also varies across markets, with emerging markets often exhibiting lower liquidity than developed ones.

A widely used metric is the bid-ask spread, which reflects the cost of immediate trade execution (Easley et al., 2016). A narrower spread indicates higher liquidity and lower transaction costs, while a wider spread implies the opposite. Studies such as Fleming (2003) and Bessembinder et al. (2006) employ this measure. Although useful, the bid-ask spread may not capture deeper complexities like hidden liquidity (Bessembinder et al., 2009). The bid-ask spread alone does not provide a complete view of liquidity, as it may not capture market depth or the ability to trade large volumes without significant price impact. Trading volume and value are fundamental liquidity metrics, with higher levels generally indicating more liquid markets due to greater participant activity. This is especially relevant for publicly traded stocks and bonds. Hasbrouck (2009) notes that higher trading volumes are typically linked to greater liquidity.

The turnover ratio, which measures the proportion of market capitalization traded over a period, also serves as a liquidity indicator. A higher ratio suggests more frequent trading and better liquidity, while a lower ratio may reflect illiquidity. Empirical studies highlight trading volume's influence on asset pricing (Amihud, 2002). Chordia et al. (2001) find that illiquid stocks are associated with lower trading activity and higher costs. Pastor and Stambaugh (2003) further show that investors require a premium for bearing liquidity risk, especially for less liquid assets. Another measure is market depth which assesses the number of buyers and sellers at various price levels. A deep market reflects greater liquidity, with a larger supply of orders ready for execution (O'Hara, 1995). In contrast, shallow markets are more vulnerable to price fluctuations from large orders. However, market depth is less applicable to OTC markets, where such order book information is not publicly available.

In the bond market, Bao et al. (2011) propose several measures of illiquidity in the U.S. bond markets. Negative covariance of price changes by trade-to-trade or daily data, gamma, is an extended version of Roll's spread measure to estimate the bid ask spread from the daily stock markets. Lin et al. (2011) examine the relationship of Amihud's illiquidity on the bond market. They find the positive relationship between the expected corporate bond market returns and liquidity risk. Liquidity risk spread accounts for a significant portion of corporate bond risk premium. Results strongly suggest that liquidity risk is an important determinant of expected corporate bond returns.

Price Jumps and Market Information

Stochastic diffusion processes have been used in the finance literature to model interest rate movements (for example, Ahn & Thomson, 1988; Cox et al., 1985). Behaviour of interest rates has long been the subject of study due to their significance in the pricing of various financial assets in the economy and its impact on macroeconomic activities as a whole. Stochastic processes allow interest rates to follow a random time series process, with the movement over time allowed to be dynamic and exhibit random movements. The random movements allowed for by the stochastic processes can be relatively small and moves proportional through time, as captured by the Brownian motion; can be autoregressive in nature, as allowed for by a complex drift component; or can be more extreme movements that occur infrequently, as captured by stochastic jump processes.

In early literature of stochastic processes involving jumps, parametric assumptions are assumed, and identified via any deviation of the data observations from the usual continuous processes. With the jump events occurring rather infrequently and unobserved, or latent, the econometric techniques involved in estimating such components are complex. Sophisticated Bayesian computation is often required for inference of such complex models, for example, Eraker et al. (2003), Eraker (2004), and Maneesoonthorn et al. (2017).

Even though stochastic jump components occur infrequently and are notoriously difficult when it comes to inference, they are an important part of the stochastic process because they contribute to the extremal risks associated with the process. In modeling interest rates, there has been growing interest in the early 2000s to account for these extreme tail behaviours. Notably, Das (2002) develops a Poisson-Gaussian jump model to explain the surprise effects in the US Federal Fund rates and found that their proposed jump model has better statistical fit properties than pure diffusion models. Johannes (2004) developed a test for jump-induced model misspecification and found jumps to play a role in a model for Treasury bill rates, with jumps coinciding with unexpected macroeconomic news.

With the availability of high-frequency data from the financial market, there has been increasing interest in the academic literature in studying the behaviour of the stochastic processes that drive financial asset prices. Of particular interest is the study of the dynamics of the variation of the price process, including any variations that may come from the extreme jump movements. Earlier work that touched on high-frequency observations include Andersen and Bollerslev (1997, 1998), along with Madhavan (2000).

The development of methodology for high-frequency financial prices exploded in the early 2000s, with the development of econometric methods that allow for high-frequency data to be used to construct various direct measures of the stochastic price process, including direct measures of volatility and jump variation. In particular, the seminal works of Barndorff-Nielsen and Shepard (2002, 2004, 2006) establish the statistical properties of such direct measures, which allow for measures of variation to be studied and explored. In addition, measures of price jump variation can be constructed directly without the need to specify a parametric model, with the statistical properties of the various measures of variation used to conduct statistical tests for jump events.

This makes studies related to the discrete jump processes much more convenient, as researchers can now avoid the inferential procedure of models with many latent variables, which is often required when working with the stochastic modeling approach. Direct measures of total volatility can now be separated into the diffusive volatility and volatility that comes from discrete and extreme jump components. Statistical tests can also be conducted based on the volatility measures constructed from high-frequency to identify jump events over a particular time horizon under question. The key advantage of this approach is the avoidance of parametric assumptions on the jump distribution, which can lead to misleading conclusions if mis-specified.

Measures of jump events are constructed by taking the difference between the total variation measure, also known as realized volatility (Barndorff-Nielsen & Shepard, 2002) and a measure of the integrated volatility that excludes variations from discrete and extreme jump events. See, for example, Barndorff-Nielsen and Shepard (2004) and Andersen et al. (2012) for alternative measures of integrated volatility. The so-called jump variation measures and their respective in-fill asymptotic properties can also be used to conduct a statistical test to assess if there is statistical evidence of jumps over a particular trade interval. Barndorff-Nielsen and Shepard (2006) pioneered the literature in this direction, with many subsequent studies developing alternative tests, see Huang and Tauchen (2005), Andersen et al. (2012), amongst others.

A review of alternative jump test performance is provided by Dumitru and Urga (2012) and, more extensively, by Maneesoonthorn et al. (2020). Both studies show that test performance is sensitive to microstructure noise, with the most robust methods being those designed to mitigate such effects. They also find that volatility jumps can affect test accuracy, with the method by Andersen et al. (2012) performing best under such conditions. These findings suggest that while the bipower variation test of Barndorff-Nielsen and Shephard (2004, 2006) is widely used, it may not be optimal in emerging markets, where microstructure noise is common.

There is an abundance of empirical studies that investigate the behaviour of jumps in financial asset prices. Jumps in the stock market are found to certainly be present and are important contributors to the predictive return distribution (Andersen et al., 2007; Maneesoonthorn et al., 2017). Jumps are also contributors to the derivative market, with the option implied volatility suggesting that extreme jump components are priced in derivative assets (Bates 1996; Busch et al., 2011; Duffie et al., 2000). This implies that investors certainly factor in risks associated with the extreme tail events in their expectation of the future, and jump components should not be overlooked in the context of market efficiency in processing information flow.

More recently, the financial econometric literature has found that jumps play a key role in predicting future return volatilities, and that that jumps exhibit time series dynamics. Patton and Sheppard (2015) proposed a model that incorporates signed jumps in predicting future volatility, and found negative jumps to be associated with higher future volatility. See also Clements and Liao (2017) and Ma et al. (2019) for similar conclusions, even when applied to different financial markets, including that of energy prices.

Previous studies primarily focus on using jump variation to forecast total return volatility. Another strand of the literature, however, models the jump process directly as a discrete-time event, showing that jump arrivals are dynamic and predictable. Maheu and McCurdy (2004) were among the first to introduce a conditionally deterministic jump arrival structure within a GARCH model. More recent work incorporates dynamic jumps through the Hawkes (1971) Poisson process. For instance, Ait-Sahalia et al. (2015) examine contagion effects on extreme tail co-movements between financial markets. Fulop et al. (2015) propose a stochastic volatility model where negative price jumps trigger jumps in volatility; and Maneesoonthorn et al. (2017) introduce a model with self-exciting jumps in both price and volatility. The broader use of Hawkes processes in finance has also been reviewed by its originator (Hawkes, 2018).

As research has revealed the dynamic nature of jumps and their link to the predictive distribution of asset prices, interest has grown in examining their relationship with market efficiency and information flow across various financial settings. Lee (2012) found that both macroeconomic and firm-specific information contribute to the predictability of jump arrivals in U.S. stock markets. Chan et al. (2014) showed that jumps in emerging market currencies are more severe than in developed markets, attributing this to lower market efficiency. Miao et al. (2014) confirmed a link between macroeconomic news and jumps in futures markets, while

Elder et al. (2013) identified a strong relationship between economic news and crude oil price jumps in the energy sector.

In the secondary bond market, jumps are often linked to information flow, particularly macroeconomic announcements. Lahaye et al. (2011) show that bond price jumps respond more strongly to new information than those in stock index futures or exchange rates. Jiang et al. (2011) find that U.S. Treasury bond price jumps are highly sensitive to liquidity shocks, with these shocks maintaining predictive power even after controlling for information flow.

Studies on bond market volatility in emerging and Asian markets remain limited. Notably, Nowak et al. (2011) examine how emerging market bond volatility responds to macroeconomic news, while Kim et al. (2021) assess how uncertainty shocks affected Asian bond markets during the COVID-19 pandemic. To our knowledge, no study has explored how information flow influences extreme price jumps in Asian bond markets. This paper fills that gap by analyzing the impact of information flow on the predictability of bond price jumps and evaluating how disclosure regulation affects this relationship.

Data Description

Thai Bond Trade Data

ThaiBMA provided three datasets covering January 2002 to December 2019. The first includes all transaction records—buyer and seller types, security symbols, prices, volumes, yields, trade and reporting timestamps, and trader classifications. While participant identities remain anonymous, entities are categorized as dealers or investors, offering insights into market composition. The data spans all bond types, including Government Bonds (GB), Treasury Bills (TB), State Agency Bonds (SA), State-Owned Enterprise Bonds (SOE), Corporate Bonds (COR), Commercial Papers (CP), Foreign Bonds (FB), and USD Bonds. The total transaction count is approximately 2.7 million, with a bond-type breakdown in Table 1.

The second dataset covers bond characteristics such as issuer, issue size, outstanding amount, coupon rate, and time to maturity. The third provides average daily indicative spreads quoted by dealers. For this study, we focus exclusively on Government Bonds (GB) to avoid confounding risk factors. We merge all three datasets, yielding a final sample of 745,911 transactions.

Table 1 Number of Transactions During 2002 to 2019.

Bond Type	**Number of Transaction**
Government bond (GB)	978,771
Treasury Bills (TB)	108,972
State Agency Bond (SA)	1,347,535
State Owned Enterprise (SOE)	27,628
Corporate Bond (COR)	225,135
Commercial Paper (CP)	21,524
Foreign Bond (FB)	4,944
USD Bond (USD)	7
All	**2,714,516**

Research Methodology

Regression Analyses of Reporting Delay and Market Liquidity

Delay is defined as the difference between the transaction and reporting times, with $delay_{j,i,t}$ denoting the delay time of the j^{th} trade of bond i and day t. To investigate the impact of mandatory reporting on the reporting delay, we estimate the following regression model**:**

$$delay_{j,i,t} = \beta_0 + \beta_1 Event1_t + \beta_2 Event2_t + \sum_{\mathrm{k}} \beta_k X_{k,i,t} + \varepsilon_{i,t} \quad (1)$$

Here, $Event_{1t}$ denotes the indicator variable that equates to 1 between January 2006 and December 2008, when mandatory reporting is in place, while $Event_{2t}$ denotes the indicator variable that equates to 1 from January 2009 onwards, when fine for late reporting is imposed. Control variables, $X_{k,i,t}$, include bond characteristics; specifically, time-to-maturity, issue size, issue term and coupon rate, respectively.

Additionally, we analyse the impact of delay in reporting on market liquidity by estimating the following regression model**:**

$$Y_{i,t} = \beta_0 + \beta_1 \overline{delay}_{i,t} + \sum_{j=1}^{2} \beta_j Event_{j,t} + \sum_{k=1}^{2} \beta_k Event_{k,t} * \overline{delay}_{i,t} + \sum_{\mathrm{k}} \beta_k X_{k,i,t} + \varepsilon_{i,t} \quad (2)$$

where $Y_{i,T}$ is daily liquidity proxy, measured by the daily turnover ratio obtained from Thai BMA.

It is important to note that while the event-study design helps isolate changes around the introduction of mandatory reporting and penalties, causality cannot be established with complete certainty. Other concurrent macroeconomic or regulatory developments could also affect market liquidity and volatility. However, during our sample period, no major policy reforms specifically targeted bond trading transparency apart from the ThaiBMA regulations, which reduces the likelihood of confounding from unrelated structural changes. We also acknowledge that our analysis does not include placebo tests or alternative liquidity measures to further validate the findings. Incorporating such robustness checks is beyond the scope of this paper but remains an important direction for future research.

Analysis of Bond Price Jumps

In this study, we adopt the jump detection technique of Barndorff-Nielsen and Shephard (2004). It is well documented that volatility can be measured using realised volatility (see Andersen & Bollerslev, 1998; Chan & Fong, 2006; Jones et al., 1994) and defined as the sum of the corresponding 1/Δ high-frequency intra-daily squared returns as:

$$RV_t(\Delta) = \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2 \quad (3)$$

where $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$ is the discretely sampled Δ-period return (5 minute return in our case) and $1/\Delta$ is the number of intradaily periods.

However, based on the theory of quadratic variation, Andersen and Bollerslev (1998) suggest that as the sampling frequency of the underlying returns increases, the realized variation converges uniformly in probability to the increment of the quadratic variation process as follows:

$$RV_t(\Delta) \to \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2 \quad (4)$$

$$RV_t(\Delta) \to \text{Integrated Variance} + \text{Jumps} \quad (5)$$

for $\Delta \to 0$, where N_t is the number of jumps on day t and $\kappa_{t,j}$ is the j-th jump size on that day.

That is, realised volatility includes the dynamics of both the continuous sample path and the jump process. However, when jump exists, it appears that realized volatility does not consistently estimate integrated volatility as it does not distinguish continuous and discontinuous components of volatility. To overcome this drawback, Barndorff-Nielsen and Shephard (2004) propose the use of bi-power variation, allowing for separation of the two components of the quadratic variation process. BNS defines the Bi-power variation, BV as the summation of the product of adjacent absolute intradaily returns standardised by a constant as follows:

$$BV_t(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} | r_{t+j\Delta,\Delta}||r_{t+(j-1)\Delta,\Delta}| \quad (6)$$

where $\mu_1 \equiv \sqrt{2/\pi}$

In the presence of discontinuous jumps:

$$BV_t(\Delta) \to \int_{t-1}^{t} \sigma^2\,(s)ds \quad (7)$$

Hence, by taking the difference between the realized variation and the bi-power variation, one can consistently estimate the jump contribution of the quadratic variation process as:

$$RV_t(\Delta) - BV_t(\Delta) \to \sum_{j=1}^{N_t} \kappa_{t,j}^2 \text{, when } \Delta \to 0 \quad (8)$$

In setting threshold for significant jump, Andersen, Bollerslev, and Diebold (2007) suggest that small jumps should be treated as measurement errors or part of the continuous sample path process and large jumps as the 'significant' jump component. In this study, we follow Huang and Tauchen (2005) and Andersen et al. (2007) by computing the Z statistic for jumps as:

$$Z_t(\Delta) \equiv \Delta^{-1/2} \frac{[RV_t(\Delta) - BV_t(\Delta)]RV_t(\Delta)^{-1}}{[(\mu_1^{-4} + 2\mu_1^{-2} - 5)\max\{1, TQ_t(\Delta)BV_t(\Delta)^{-2}\}]^{1/2}} \quad (9)$$

where

$$TQ_t(\Delta) \equiv \Delta^{-1}\mu_{4/3}^{-3} \sum_{j=3}^{1/\Delta} | r_{t+j\Delta,\Delta}^2|^{4/3}|r_{t+(j-1)\Delta,\Delta}^2|^{4/3}|r_{t+(j-2)\Delta,\Delta}^2|^{4/3} \quad (10)$$

And

$\mu_{4/3} = 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$, $TQ_t(\Delta)$ is the integrated quarticity.

BNS demonstrates that the integrated quarticity may be consistently estimated using equation (8). Under the null hypothesis of no jumps, $Z_t(\Delta)$ is approximately normally distributed. To detect significant jumps, we compare the test statistics to a standard normal distribution with our chosen significance level α and create an indicator variable [5],

$$I_{t,\alpha}(\Delta) = I[Z_t(\Delta) > \Phi_\alpha], \tag{11}$$

as a measure of jump event. In addition, we measure the jump variation as

$$JV_t = \max\,(RV_t - BV_t, 0) \tag{12}$$

as a proxy for jump size. While alternative measures of the integrated variance, such as those of Andersen et al. (2012), can be constructed, the sparse trade in the Thai bond market is not amendable to these alternatives. We are unable to construct high-frequency returns at a frequency that is high enough to exploit these alternatives, and thus we opt to use the traditional BNS framework to preserve the in-fill sample size to maximize the power of jump tests.

We analyse the change in the probability of jump event and the jump size by first analyzing their means and construct the confidence interval using bootstrap overcome the issue of small sample size. In addition to the analysis of the mean differences of the jump variation, we also conduct a regression analysis that controls for the key covariate of time to maturity of the bond to assess the impact of mandatory reporting on the perceived jump size. We consider the linear regression for jump size:

$$\log(JV_t) = \beta_0 + \beta_1\,Event_{1t} + \beta_2\,Event_{2t} + \beta_3 TTM_t + \varepsilon_t \tag{13}$$

With newly issued bonds tending to be "on-the-run" with larger trade activities, and bonds closer to maturity tending to be "off-the-run" and are less active, our jump analysis controls for this phenomenon in two ways. First, the time to maturity (TTM) serves as the key control variable for this phenomenon. Secondly, all jump measures are constructed relative to the local volatility of the period. The volume of trading activities impacts the overall stochastic movement of the pricing process, and thus, controlling for the local volatility in the jump measure also, to some extent, controls for the impact of changing trade dynamics in the market.

Research Findings

Analysis of Delay

We compute the time intervals by subtracting the trade time from the report time for each transaction. Table 2 illustrates the distribution of these time gaps. On the left side of the table are transactions exhibiting negative time gaps, totaling 5,598 instances. Notably, most of these discrepancies, accounting for 3,334 out of 5,598 observations, occur within an hour. Such inconsistencies may stem from human or typographical errors, and we exclude these transactions in all of our analyses.

[5] The smaller the significant level α, the lesser and larger (in magnitude) jumps we have.

Conversely, the right side of Table 2 showcases transactions with positive time gaps. The first and second rows denote instances where transactions are reported within 15 and 30 minutes, respectively. We observe 583,566 and 58,000 occurrences out of 745,911 total observations, indicating that the majority of reporting transactions adhere to the regulatory requirement of within 30 minutes.

Transactions beyond the 30-minute mark are considered delayed. Notably, the majority of these delayed reports, totaling 33,014, 34,113 and 13,390 transactions, respectively, occur within 3 hours. It is worth noting that delayed reports may stem from transactions occurring both before and after 15:30, with regulations requiring reporting within 30 minutes on the same day or before 9:30 on the following business day, respectively.

Table 2 Time Gap Between the Trade Time and Report Time in Minutes.

Report Time Gap	Freq	%	Report Time Gap	Freq	%
< Neg 6 Hrs	257	0.034%	0:00 Hrs	11,931	1.600%
Neg 6:00 Hrs	191	0.026%	0:15 Hrs	571,635	76.636%
Neg 5:00 Hrs	353	0.047%	0:30 Hrs	58,000	7.776%
Neg 4:00 Hrs	435	0.058%	1:00 Hrs	33,014	4.426%
Neg 3:00 Hrs	505	0.068%	2:00 Hrs	34,113	4.573%
Neg 2:00 Hrs	523	0.070%	3:00 Hrs	13,390	1.795%
Neg 1:00 Hrs	3,334	0.447%	4:00 Hrs	5,863	0.786%
			5:00 Hrs	3,726	0.500%
			6:00 Hrs	1,764	0.236%
			> 6:00 Hrs	6,877	0.922%
Total	5,598	0.750%	Total	740,313	99.250%

Table 3 presents the number of long delay reports recorded each year along with their total value in billion Baht. In the regular cases, when the transaction is completed and reported subsequently, the delay is positive. However, to be in line with Table 2, we use the 6 hour threshold in this table. Panel A shows the results by year and panel B shows the results by trade type which are buy or sell transactions. Similar to the negative delay reports, the occurrence of positive delay reports was high at the beginning in 2002 and 2003, peaking at 2,367 in 2002 and 1,004 in 2003. Notably the occurrences dropped significantly when the regulation was implemented and penalty was enforced. However, our findings indicate periodic increases in long delay reports both in frequency and amount. Panel B categorizes the positive delay reports. We find that there are 3,283 buy transactions with a total value of 127 billion Baht, and 3,572 sell transactions with a total value of 149 billion Baht.

We regress the reporting delay of each transaction on dummy and control variables, excluding observations with negative delays or delays exceeding 6 hours due to their small sample size (each less than 1%), which could introduce confounding effects. Control variables include: TTM (time to maturity in years), Issue Size (bond issue value in million Baht), Coupon (coupon rate as a percentage of face value), and Issue Term (bond's term in years). Regression results are shown in Table 4. The coefficients for both Event 1 and Event 2 are significantly negative at the 1% level, indicating that, relative to the pre-2006 period, reporting delays declined by 49 and 59 seconds during 2006 to 2009, respectively, reflecting the regulatory effectiveness of ThaiBMA.

Although the magnitude of these reductions may appear modest in absolute terms, even small improvements in reporting timeliness can have meaningful economic implications in thinly traded bond markets. Faster dissemination of trade information reduces information asymmetry, enhances investor confidence, and strengthens the credibility of regulatory oversight. By narrowing the window in which dealers might exploit delayed reporting, the regulation contributes to market stability and fairer trading conditions.

Table 3. Statistics of Long Delay Reports

Panel A. Number of Observations with Long Delay Reports and Value of Transactions by Year.

Year	Delayed Report (>6:00Hrs)	Value (Billion Baht)
2002	2,367	55.433
2003	1,004	22.770
2004	491	15.563
2005	475	15.033
2006	319	13.506
2007	554	27.839
2008	128	7.349
2009	89	4.426
2010	198	11.714
2011	130	13.126
2012	110	11.725
2013	205	18.268
2014	145	12.623
2015	166	9.736
2016	112	11.676
2017	102	5.758
2018	129	8.360
2019	131	10.672

Panel B. Number of Observations with Long Delay Reports and Value of Transactions Categorized by Type of Trades

Trade Type	Delayed Report (>6:00Hrs)	Value (Billion Baht)
B	3,283	127.006
S	3,572	148.569

Focusing on the control variables, longer time to maturity and higher coupon rates are linked to longer reporting delays, while long-term bonds are associated with shorter delays. Further analysis shows variation in reporting behavior across dealer groups: Dealer 1 (BankF) exhibits longer delays, whereas Dealer 2 (NDL) reports more promptly than the control group (SEC). Transactions on Wednesdays and Thursdays are more likely to be delayed than those on Mondays, suggesting a day-of-the-week effect. Additionally, trades between dealers and clients tend to have shorter delays, as the dealer bears responsibility for reporting to ThaiBMA.

Table 4: The Effect of Regulation on Reporting Delay

Parameter	Estimate	StdErr	t-Value	Prob
Intercept	62.0601***	2.4732	25.0931	0.0000
Event1	-49.5760***	2.1804	-22.7370	0.0000
Event2	-59.2590***	0.8398	-70.5627	0.0000
TTM	0.4243***	0.0859	4.9374	0.0000
Issue Size	0.0001	0.0000	-0.4123	0.6812
Coupon	1.4411***	0.4069	3.5415	0.0007
Issue Term	-0.4772***	0.0766	-6.2303	0.0000
Dealer BankL	0.2064	1.2551	0.1645	0.8698
Dealer BankF	5.8511***	1.4435	4.0535	0.0001
Dealer NDL	-24.2625***	1.8997	-12.7719	0.0000
Tue	-0.0228	0.2544	-0.0898	0.9287
Wed	0.5366***	0.1999	2.6842	0.0088
Thu	0.6699***	0.2181	3.0713	0.0029
Fri	0.3740	0.2923	1.2797	0.2043
Dummy D2C	-1.7314*	0.9530	-1.8168	0.0729

Notes. ***, *, * denote significance at the 1%, 5%, and 10% levels, respectively

Analysis of Liquidity

We calculate turnover as transaction volume divided by the outstanding bond amount, providing a relative measure of actual trading activity and a useful proxy for liquidity. Figure 1 (Panel B) illustrates the turnover ratio for bonds traded from January 2002 to December 2019. Two vertical red dotted lines mark key regulatory dates: January 1, 2006, when trade reporting became mandatory, and January 1, 2009, when penalties for non-compliance were introduced. Turnover ratios trend upward over time but remain volatile. Prior to 2006, fluctuations are frequent and pronounced. Following the 2006 reporting mandate, turnover becomes more volatile but increases on average, suggesting higher market activity and liquidity. After the 2009 penalty enforcement, the upward trend continues. Overall, bond market liquidity was initially unstable but improved over time, as evidenced by a declining spread and rising turnover ratio during the final decade of the study.

To further examine the regulatory impact on government bond market liquidity, we estimate the model in Equation (2), using turnover ratio as the dependent variable. Results are presented in Table 5. Overall, reporting delay is positively associated with turnover—suggesting that longer delays correlate with greater market liquidity. Interestingly, regulation appears to have an adverse effect on liquidity. Event 1 is significantly positive, with a 46 basis point increase in turnover, while Event 2 (post-2009, when penalties were introduced) shows no significant change relative to the pre-2006 period. This may reflect the high volatility of turnover during the sample period. We speculate that higher turnover may signal increased activity from large traders, which could draw additional market participants. Dealers executing such trades may be more inclined to delay reporting.

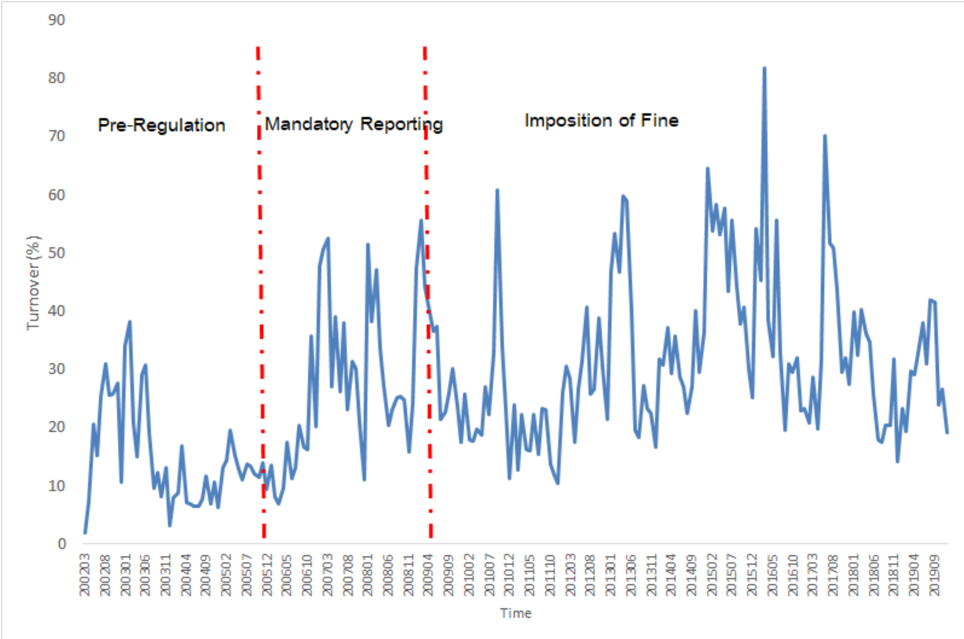

Figure 1. Average Daily Turnover Ratio of Bond Trading from 2002 to 2019.

Table 5: The Effect of Regulation and Reporting Delay on Liquidity

Parameter	Estimate	StdErr	t-Value	Prob
Intercept	0.0047	0.0071	0.6657	0.5077
Delay	0.0001**	0.0000	-2.2910	0.0248
Event1	0.0046**	0.0020	2.2828	0.0254
Event2	0.0001	0.0025	0.0173	0.9862
TTM	-0.0016***	0.0005	-3.6007	0.0006
IssueSize	0.0000*	0.0000	-1.7267	0.0884
Coupon	0.0011	0.0014	0.8225	0.4134
Issue Term	0.0015***	0.0005	3.1443	0.0024
Dealer BankL	0.0009*	0.0005	1.8820	0.0638
Dealer BankF	0.0006	0.0005	1.2598	0.2117
Dealer NDL	-0.0007	0.0008	-0.9070	0.3674
Tue	0.0003*	0.0002	1.8793	0.0642
Wed	0.0022***	0.0004	5.3971	0.0000
Thu	0.0008***	0.0002	3.5407	0.0007
Fri	0.0009***	0.0003	3.2926	0.0015
Dummy D2C	0.0013*	0.0006	1.9646	0.0533

Notes. ***, *, * denote significance at the 1%, 5%, and 10% levels, respectively

Analysis of Price Jumps

To evaluate our jump-related hypotheses, we construct realized measures using high-frequency data for a select subset of government bonds. Given the importance of high-frequency data for measurement accuracy, we choose bonds that span the pre-regulation period, the threat period (regulation without fines), and the enforcement period (with fines). The selected bonds are actively traded, averaging at least 40 trades per day. Table 6 summarizes the government bonds used. For all four bonds, we examine jump behavior across three phases:

the pre-regulation period (before January 2006), the mandatory reporting phase without penalties (January 2006–December 2008), and the post-penalty period (January 2009 onward). Although this study of price jumps is limited to four bonds, we have chosen the selected bonds carefully to preserve the statistical rigor of our jump measures, while being able to track the impact of the regulations over time.

Table 6: The List of Government Bonds Used to Conduct Jump Activity Analysis

Bond	Number of Trading Days	Start	End
LB11NA	1280	12/03/2002	16/11/2011
LB104A	929	6/03/2002	24/03/2010
LB12NA	781	13/11/2002	16/10/2012
LB113A	820	6/03/2002	16/02/2011

We construct realized volatility and bipower variation to perform the price jump test, using a 1% significance level throughout. Figure 2 shows weekly percentage changes in bond prices, realized variation, jump variation, and detected price jumps for Bond LB11NA, the bond with the longest trading period in our sample. Each panel includes two vertical red dotted lines marking key regulatory events: the introduction of mandatory reporting and the imposition of fines. As the four bonds were traded over different periods, the positions of these lines vary by figure. A striking observation emerges: only one weekly jump is detected across all four bonds after mandatory reporting began. Jump variation (JV) also declines in magnitude for the bonds analysed. These patterns persist across the other bonds in the sample.

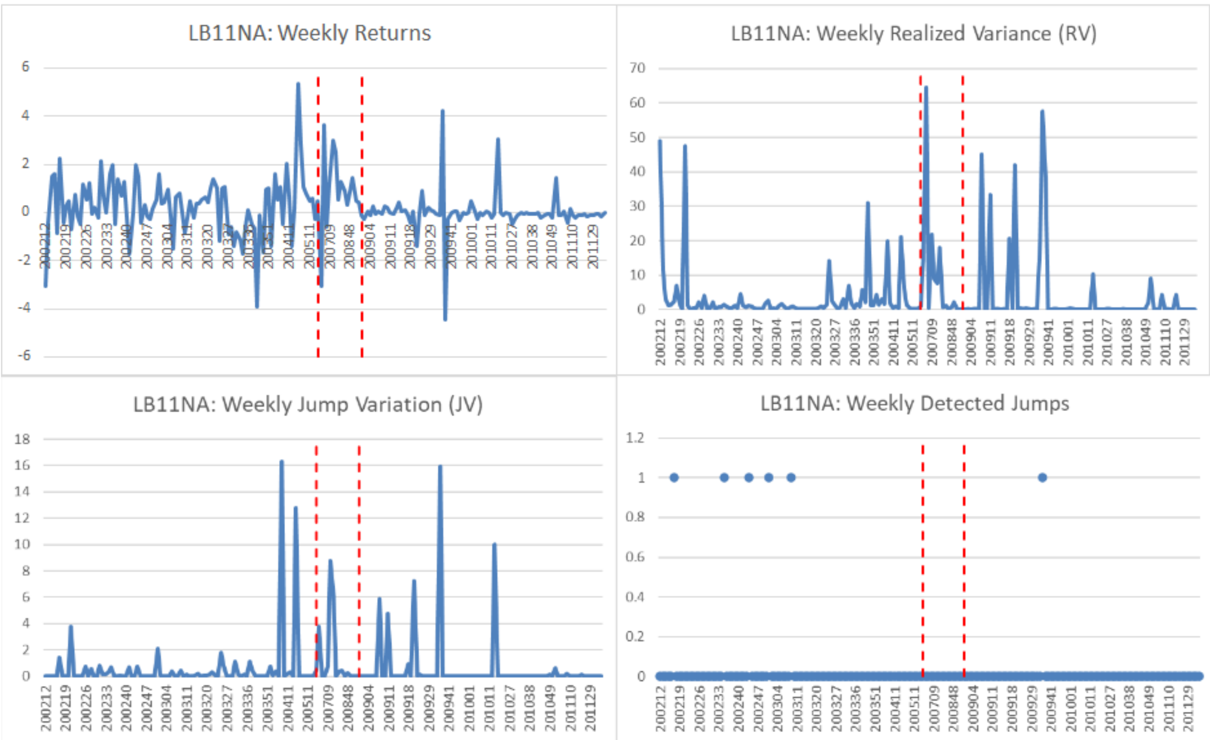

Figure 2: Returns, RV, JV and Detected Jumps for LB11NA

The jump frequency implied by the BNS jump test is then summarized and reported alongside its confidence interval, constructed using the blocked bootstrap to retain any dependency of jump occurrences over time. Likewise, we also report the resulting variation attributed to jumps for the corresponding bonds and period, with the mean jump variation reported alongside the bootstrap confidence interval. Both jump frequency and jump variation statistics are reported in Table 7.

Table 7: Summary of Jump Frequency and Jump Variation for the Three Phases of the Regulation. We Report the 95% Bootstrapped Confidence Interval along with the Sample Mean of Each Quantity.

	Bond	Pre-Regulation	Mandatory Reporting	Imposition of Fine
Jump Frequency	LB11NA	0.0532	0.0000	0.0118
		(0.0213,0.0957)	(0,0)	(0,0.0353)
	LB104A	-0.0481	0.0000	0.0000
		(0.0096,0.0962)	(0,0)	(0,0)
	LB12NA	0.0943	0.0000	0.0000
		(0.0377,0.1698)	(0,0)	(0,0)
	LB113A	0.0494	0.0000	0.0000
		(0.0123, 0.0864)	(0,0)	(0,0)
Jump Variation	LB11NA	0.5347	1.3899	0.5412
		(0.2008, 1.0764)	(0.3713,2.4085)	(0.1594,0.9868)
	LB104A	0.7297	1.8610	0.0010
		(0.1788,1.3169)	(0.5940,3.1280)	(0.0004,0.0017)
	LB12NA	1.1900	27.3366	6.3865
		(0.3780,2.1798)	(3.7413,50.9318)	(0.2961,12.6427)
	LB113A	0.8281	0.9233	0.1980
		(0.2823,1.5101)	(0.2371, 1.6093)	(0.0006,0.3954)

Table 7 shows a notable decline in jump frequency following the introduction of mandatory trade reporting in 2006. For three of the four bonds analysed, no jumps were detected after 2006, suggesting that unexpected price movements subsided once reporting was enforced. This pattern continues after the implementation of late-reporting penalties. Regarding jump variation—measured as the difference between realized volatility (RV) and bipower variation (BV)—a general decline is observed post-regulation, with the exception of LB12NA. Our findings indicate that regulation impacts extreme price movements. There is strong evidence of a reduction in the frequency of such jumps, with confidence intervals confirming a significant decline in extreme, unexpected price shifts following mandatory reporting. The magnitude of these movements also appears to decrease, as shown by the narrowing gap between RV and BV.

From the regression analysis, the control covariate is the time to maturity of each bond, controlling for both bond characteristics and the "on-the-run" trading behavior that is inherent in newly issued bonds. Table 8 reports the results from the regression, with the coefficient estimate reported along with the associated p-values in parenthesis. For three out of the four bonds investigated, the slope coefficients of the $Event_{2t}$ indicator are negative, while the slope coefficients for the $Event_{1t}$ indicator showed mixed signs. Only one of the negative coefficients of the $Event_{2t}$ indicator is statistically significant. From this analysis with controlled covariates, we observe that the degree of jump variation is impacted by the introduction of the fine for only one out of the four bonds considered. No significant impact was observed on jump variation with the mandate of the reporting without penalty. The observation of mixed results on jump size is not surprising, given the fact that there are very few detected jumps after the introduction of the fine, as demonstrated by the analysis of the jump occurrences. Taken together, these results suggest that the regulatory impact on jump size is not uniform across all bonds, and therefore strong conclusions about reductions in jump magnitudes cannot be drawn. By contrast, the evidence on jump frequency is far more consistent, with a clear reduction in the occurrence of extreme price movements after the reporting regulations. We therefore interpret the regulations as being most effective in reducing the likelihood of jumps, even if the effect on jump magnitudes is less conclusive

Table 8: Regression Results for Assessment of the Impact of the Introduction of the Regulations and Fine on the Magnitude of Jump Variation, Controlling for the Time to Maturity of the Bond.

Bond Symbol	Coefficients			
	Intercept	Event1	Event2	TTM (years)
LB11NA	-4.9670*	3.5470*	1.4827	0.3756
	0.0833	*0.0460*	*0.5277*	*0.2513*
LB104A	1.2742	-1.3839	-6.4699*	-0.4221
	0.6480	*0.5253*	*0.0517*	*0.2881*
LB12NA	-0.1213	3.0198	-0.7898	-0.0476
	0.9830	*0.4009*	*0.8530*	*0.9380*
LB113A	1.1076	0.8819	-2.3614	-0.3035
	0.7478	*0.7022*	*0.4403*	*0.4754*

Notes. ***, *, * denote significance at the 1%, 5%, and 10% levels, respectively

Discussions and Conclusion

Transparency and timely information play a critical role in the functioning of financial markets, especially in the bond market, where large fund flow is at stake. The accuracy and timeliness of information is desirable as it promotes market liquidity and stability as well as assists investors to make an informed investment decision. Recognizing the importance of these issues, regulators around the world, including Thailand have introduced regulatory framework to promote market transparency. Recent corporate scandal by the Stark corporations undermines investors' confidence and causes the large fund flow out of the Thai bond markets[6]. This highlights the importance of market transparency and appropriate policies imposed by the regulator. Motivated by these and mixed evidence of reporting time, we study the transaction level of the Thai government bonds and provide empirical evidence on how mandatory reporting requirements impact the tendency to delay reporting, market liquidity and price jumps. Overall, we find mandatory reporting and penalty enforcement has a significant positive impact on the Thai bond market by reducing delay reporting, enhancing liquidity and mitigating extreme price jumps. The reduction in extreme price jumps is particularly important,

[6] See Securities and Exchange Commission, Thailand. (6 July 2023). "*SEC files a criminal complaint against 10 offenders with the DSI for falsifying STARK financial statements, making false statements in the registration statements, and acting in the manner that dishonestly deceives others*." Retrieved from https://www.sec.or.th/EN/Pages/News_Detail.aspx?SECID=10553

as it lowers tail-risk exposure for investors. Fewer abrupt and unpredictable movements strengthen market confidence, encourage broader participation, and reduce the risk premium demanded by investors. For issuers, this may translate into a lower cost of capital and more stable access to funding.

Our findings underline the importance of transparency and timeliness of information in promoting market liquidity and stability and have several implications to various stakeholders, including bond investors, issuers and regulators. For instance, the improved liquidity and reduced volatility associated with mandatory reporting and penalties enforcements can benefit investors to make a more accurate price forecast and less exposed to the extreme price risk, making their investment more secured. Likewise, bond issuers can also benefit from this by having lower cost of capital and easier access to funding with the enhanced investors' confidence associated with the mandatory reporting and penalties enforcement. Finally, regulators' access to timely information enhances their ability to enforce post-trade transparency in line with international best practices, such as those recommended by the International Capital Market Association (ICMA), thereby fostering greater investor confidence in the growing Thai bond market[7].

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[7] See ICMA (2020), Recommendations for post-trade transparency in the secondary bond markets, available at https://www.icmagroup.org/assets/documents/Regulatory/Secondary-markets/ICMA-Post-trade-transparency-recommendations-2020.pdf

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