The Components of Bid-Ask Spread in Thailand's Government Bond Market*

Anya Khanthavit**

Abstract

Bid-ask spread can be decomposed into permanent and transitory components. In this study, I estimate the spread's permanent and transitory components in Thailand's government bond market--using daily bid and ask yields from January 2, 2003 to August 22, 2014, and relate them respectively with asymmetric-information and inventory-control costs being incurred by dealers. The inventory-control components exhibit a J-shaped relationship with bond tenors. Their levels and percentage shares fall to almost zero for 5- to 10-year bonds. The asymmetric-information components are correlated positively with dealer-to-client trading volume to which asset management companies contribute most.

Keywords: Bid-Ask Spread, Permanent and Transitory Components, Government Bond Market

^{*} The author thanks the Faculty of Commerce and Accountancy, Thammasat University for the research grant, thanks Tanachote Boonvorachote, Manapol Ekkayokkaya and Pranee Leksrisakul for comments, thanks the Thai Bond Market Association for the data and thanks Trirat Puttaraksa and Phatid Rongsirikul for research assistance. The author can be reached at the Faculty of Commerce and Accountancy, Thammasat University, Bangkok, Thailand 10200 or at akhantha@tu.ac.th.

^{**}Distinguished Professor, Department of Finance, Thammasat Business School, Thammasat University

ส่วนประกอบของส่วนต่างระหว่างราคาเสนอซื้อและเสนอขาย ในตลาดพันธบัตรรัฐบาลไทย

อัญญา ขันธวิทย์**

บทคัดย่อ

ส่วนต่างระหว่างราคาเสนอซื้อและเสนอขาย สามารถแยกส่วนประกอบออกได้เป็นส่วนที่ส่งผลต่อ การเปลี่ยนแปลงของราคาชนิดถาวรและชนิดชั่วคราว ในการศึกษา ผู้วิจัยได้กำหนดส่วนประกอบชนิดถาวร และชนิดชั่วคราวสำหรับส่วนต่างของราคาเสนอซื้อและ เสนอขายพันธบัตรรัฐบาลในตลาดตราสารหนี้ไทย โดยใช้ ข้อมูลส่วนต่างอัตราดอกเบี้ยเสนอซื้อและเสนอขายเป็น รายวัน ตั้งแต่วันที่ 2 มกราคม พ.ศ. 2546 ถึงวันที่ 22 สิงหาคม พ.ศ. 2557 จากนั้นเชื่อมโยงส่วนประกอบทั้งสอง เข้ากับต้นทุนที่ผู้ค้าตราสารหนี้แบกรับจากการที่ตนมีข่าวสาร ข้อมูลที่ด้อยเมื่อค้า และจากการที่ตนต้องบริหารการถือ ครองตราสารหนี้เพื่อการค้า ผู้วิจัยพบว่าส่วนประกอบ สำหรับต้นทุนจากการบริหารการถือครองตราสารหนี้มี ความสัมพันธ์รูป J กับอายุคงเหลือของพันธบัตร โดยที่ ระดับและสัดส่วนคิดเป็นร้อยละในส่วนต่างของราคาลด ลงจนเกือบเป็นศูนย์สำหรับพันธบัตรอายุ 5 ถึง 10 ปี และพบว่า ส่วนประกอบสำหรับต้นทุนจากการมีข้อมูล ข่าวสารที่ด้อย มีความสัมพันธ์เชิงบวกกับปริมาณการซื้อ ขายที่เกิดจากการค้าระหว่างผู้ค้ากับลูกค้า โดยเฉพาะ บริษัทจัดการลงทุน

คำสำคัญ: ส่วนต่างระหว่างราคาเสนอซื้อและเสนอขาย ส่วนประกอบที่ส่งผลต่อการเปลี่ยนแปลงของราคาชนิดถาวร และชนิดชั่วคราว ตลาดพันธบัตรรัฐบาล



^{**}ศาสตราจารย์ประจำภาควิชาการเงิน คณะพาณิชยศาสตร์และการบัญชี มหาวิทยาลัยธรรมศาสตร์

1. Introduction

Bid-ask spread is of great interest to practitioners and regulators in Thailand's bond market. As was suggested by Fleming (2003), spread is the best indicator of trading liquidity which is one of the most desirable properties of a market. For practitioners, spread is income earned by dealers and cost incurred by investors. And for regulators, understanding the structure of spread helps to shape policy making and market design for enhancing market quality.

Spread can be decomposed into asymmetricinformation and inventory-control components. The asymmetric-information (AI) components arise in order to compensate dealers for incurring losses from possible trading with informed traders, while inventory-control (IC) components do in order to compensate dealers for incurring costs from order processing and from inventory-related risk and management. See, for example, Foucault, Pagano and Roell (2013), chapter 3.

Previous studies estimated the components of bid-ask spread in several markets based on competing market microstructure theories and alternative econometric techniques. Most of these studies considered developed stock markets, high-frequency data, and regressions of prices on lagged prices and trade directions (Foucault et al., 2013, chapter 5). These studies agreed that AI components were dominant in the spread. The studies for bond markets--especially those in emerging countries, are few. And there is no study on the components of bid-ask spread for Thailand's bond market.

In this study, I estimate the components of bid-ask spread for Thailand's government bond market. The contributions are at least two folds. Firstly, Thailand's government bond market is one of the most important markets in Asia.¹ In the sample countries of *Asia Bond Monitor* (Asian Development Bank, 2014), in the first quarter of 2014 Thailand's government bond market ranked fourth in terms of size after Japan, China and Korea. This study is first to estimate the components of bid-ask spread in Thailand's government bond market. The estimation is possible thanks to the unique dataset of bid and ask government-bond yields constructed exclusively for this study by the Thai Bond Market Association.

Secondly, as was measured by average bid-ask spread, in 2013 the trading liquidity of Thailand's market ranked third after Korea and India's for on-the-run bonds and ranked third after Korea and Singapore's for off-the-run bonds (Asian Development Bank, 2013). Despite the relatively high trading liquidity, lower bid-ask spread, higher trading

¹ Similar to the U.S.A. market, Thailand's bond market is a dealer market in which most trading is conducted over the counter. Trading activities can be via dealers' quotation through telephone, vendor screens or BEX facilities. The largest client group in terms of trading volume is asset management companies. See the Asian Bonds Online and the Thai Bond Market Association's websites for further details.

liquidity, and better quality of the market are always desirable for Thailand so that the market competes successfully with other national and international markets. The findings of this study about the relative importance of each component help the regulators to improve the market designs and to devise the market policies in appropriate ways.

In the estimation, I follow Choi, Lee and Yu (1998) to decompose the bid-ask spread into permanent and transitory components and estimate these two components from the percentage bid and ask spread using Kalman filtering. Then I relate them respectively with AI and IC components based on market microstructure theories, e.g. Glosten and Harris (1988). The theories explain that, on the one hand, the IC components generate income for dealers from a seemingly random order flow to cover inventory costs, order processing fees, and inventory-related risk. The IC components should be transitory components because their effects on the price time series are unrelated with the true value of the bond. On the other hand, the AI components compensate for possible losses incurred by dealers from trading with informed traders who know the true value. AI components should be permanent because they provide permanent effects on all future prices.

Using the daily bid-and-ask-yield data for Thailand's government bond market from January 2, 2003 to August 22, 2014, I find that the average percentage spread is rising with bond tenors. The inventory-control components exhibit a J-shaped relationship with the tenors. Their levels and percentage shares fall to almost zero for 5- to 10-year bonds. The asymmetric-information components are correlated positively with dealer-toclient trading volume to which asset management companies contribute most. Based on these findings, I conclude for Thailand's bond market that (1) the order-processing costs residing in the IC components are very small, (2) the low liquidity of short and long bonds are due to their low floating supply and (3) clients--especially asset management companies, not dealers are informed traders.

2. The Model

In the literature, most studies on the components of bid-ask spread use high frequency data and regress prices on lagged prices and trade directions in their analyses. See Foucault et al. (2013), chapter 5 for a review. But these high frequency data for the bond market are not available in Thailand. To proceed, I will have to work with the bid-ask spread and follow Choi et al. (1998) to decompose it into permanent and transitory components.² I then relate the compositions respectively with AI and IC components so that the bid-ask spread BAS_t at time t is the sum of AI

 $^{^{2}}$ Because the bid-ask spread is the difference of bid and ask prices, the permanent components cancel so that the spread becomes a stationary time series. The percentage spread reintroduces the permanent components to the series from the mid-point price denominator.

component AI_t and IC component IC_t as in eq. (1). Madhavan and Smidt (1991), for example, propose a theoretical model to describe dealer behavior that incorporates the effects of both information asymmetry and inventory.

$$BAS_{t} = AI_{t} + IC_{t}.$$
 (1)

 AI_t follows a random walk process in eq. (2) because it affects the bond price permanently due to information brought into the market by informed traders.

$$AI_{t} = AI_{t-1} + w_{t}, \qquad (2)$$

where w_t is the error term. It is assumed w_t is distributed normally with a zero mean and a σ_w standard deviation.³ I impose a zero drift for the random walk process because the drift is the expected change of AI_t. A non-zero drift implies that AI_t and BAS_t increase or decrease without bound. But this is not possible. AI_t and BAS_t cannot be negative. And they cannot grow beyond 100 percent of the par value. A driftless random walk is commonly assumed for the permanent part of asset price, e.g. Hasbrouck (1993). I do not use the specification in Choi et al. (1998) for AI_t because it is complicated but provides little more insight in the analysis.⁴ IC_t is transitory. I assume it follows a mean-reversion process in eq. (3).

$$IC_{t}-IC_{t-1} = \rho(\mu - IC_{t-1}) + e_{t},$$
(3)

where the error term e_t is distributed normally with a zero mean and a σ_e standard deviation. e_t is uncorrelated with w_t . μ can be interpreted as being the expected value of IC_t to which IC_t converges. ρ is the speed of convergence of IC_t to μ if IC_t deviates from it. A mean-reversion process is popular in studies of interest rate behavior. The process should be applied well to describe the behavior of IC_t. In an inventory-control model such as Amihud and Mendelson (1981) and Ho and Stoll (1981), dealers adjust the spread through IC_t so that their inventory reverts to its optimal level. Moreover, μ helps to identify the appropriate level of IC_t and to differentiate it from the level of AI_t.

3. The Estimation

I cannot observe AI_t or IC_t . So in the estimation I will have to work with BAS_t --the only variable that can be observed in the model. Combining eqs. (1) and (3) gives the measurement equation in (4).

³ A normality assumption is not necessarily inconsistent with the 0%-lower and 100%-upper bounds for the spread. The assumption can be made if the probability for the variable to take on a large negative or positive value is small.

 $^{^4}$ Choi et al. (1998) assume the shock w_t follows a random walk process. This assumption is not required by the theory. Imposing this assumption adds one more transition equation in the estimation.

$$BAS_{t} = AI_{t} + \rho\mu + (1 - \rho) IC_{t-1} + e_{t}.$$
 (4)

Eq. (2) is the transition equation. Eqs. (2) and (4) constitute a state-space model which can be estimated by Kalman filtering. The filtering works in two steps. In the first step, the filtering estimates the expectations of AI_t and IC_t as well as their error terms based on eqs. (2) and (3). In the second step, the expectations of AI_t and IC_t are updated with current BAS_t after it is observed. The filtering operates recursively for the remaining observations. The two-step procedure produces statistically optimal estimates of AI_t and IC_t . See Harvey (1989) for details.

4. The Data

In the literature, the estimation of AI and IC components is generally based on high frequency, transaction price and trade data. However, these data are not available for Thailand's bond market. The data available to me are daily bid and ask yields for government bonds. Although the daily data are not high-frequency, the analysis should not be affected much because trading activities during the day are not very high.

The data are constructed by the Thai Bond Market Association to be used for the first time in this study. They are from January 2, 2003 to August 22, 2014 (2847 daily observations).⁵ I consider the bonds of 1-, 3-, 5-, 7-, 10-, and 15-year tenors. All the sample tenors except for the 1-year tenor are benchmark ones. The 1-year tenor is added to the sample to represent short-term bonds.

I follow Choi et al. (1998) to convert bid and ask yields into percentage bid-ask spread so that the permanent component in the spread is preserved. The bond price $B_t(\tau)$ at time t for tenor τ is computed by $B_t(\tau) = e^{-y_t(\tau) \times \tau}$, where $y_t(\tau)$ is the yield at time t for tenor τ . The spread is the difference between the bid and ask prices. It is converted to percentage spread by the average of bid and ask prices.

Table 1 reports the descriptive statistics of bid-ask spread for the sample bonds. The average spread is increasing with bond tenors. The average for 1-year tenor is smallest of 0.05 basis point, while that for 15-year tenor is highest of 1.25 basis points. The standard deviations of the spread are increasing with tenors as well.

I reject the normality hypothesis by Jarque-Bera (JB) tests for all the tenors at a 99% confidence level. I also check for the non-stationarity

⁵ If bonds are traded infrequently, spread can stale. Nevertheless, stale spread should not be a problem in this study due to two reasons. Firstly, the daily bid and ask yields reported by the Thai BMA are executed yields. If the bonds are not executed on the day, the yields are always available from dealer polling. Secondly, among the 2847 observations, there are only 42, 7, 94 and 277 non-trading days for 0-to-3 year, 3-to-7 year, 7-to-10 year and more-than-10 year tenors, respectively.

property which should be found for the spread with permanent components. If the spread is nonstationary, the AR(1) coefficient must be 1.00. I estimate the AR(1) coefficients and find that they are high and close to 1.00 for all the tenors. I also test for the non-stationarity hypothesis. Despite the fact that the AR(1) coefficients are almost 1.00, the Dickey-Fuller (DF) tests reject the non-stationarity hypothesis at a 99% confidence level. The rejection may be due to biasedness of the tests or small contribution of permanent components to the spread.

5. Empirical Results

5.1 Parameter Estimates

I estimate the state-space model in eqs. (2) and (4) by the Kalman filter. The model parameters are reported in Table 2.

Turn first to μ -the long-run expected value of IC_t. It is interesting to find that IC costs are relatively high for short bonds of 1- and 3-year tenors. But they drop to about zero for 5-, 7- and 10-year bonds and rise quickly to 4.33 basis points for 15-year bonds. High μ 's correspond with high

Tenor	Average	Min	Max	STD	Skew	Kurt	JB Stat	AR(1)	DF Test
1Y	0.0527	0.0160	0.1798	0.0215	0.9653	1.3323	652.6894^{***}	0.9197	-10.9185***
3Y	0.2100	0.0326	1.1060	0.0978	2.0131	12.5005	20459.6019^{***}	0.9530	-8.2950***
5Y	0.3174	0.0634	1.1017	0.1189	0.3375	1.3356	265.6332^{***}	0.9132	-11.3665***
7Y	0.5053	0.0834	2.5384	0.1984	1.2939	7.5514	7558.8834^{***}	0.8989	-12.3259***
10Y	0.7210	0.1181	2.8398	0.2905	1.5744	6.8266	6704.3248^{***}	0.9289	-10.2560***
15Y	1.2572	0.3955	4.3298	0.4503	1.4395	5.8827	5088.3907^{***}	0.9425	-9.1558***

Note: *** = Significant at a 99% confidence.

Table 1 Descriptive Statistics

Table 2 Model Parameters

Tenor	μ	ρ	$\sigma_{ m w}$	σ_{e}
1Y	0.1273	0.1267^{***}	0.0048^{***}	0.0053^{***}
3Y	0.8740	0.0540^{***}	0.0223^{***}	0.0144^{***}
5Y	1.58E-08	0.1681^{***}	0.0278^{***}	0.0307^{***}
7Y	2.23E-07	0.1163^{***}	0.0478^{***}	0.0560^{***}
10Y	1.61E-06	0.1387^{***}	0.0569^{***}	0.0693^{***}
15Y	4.3298^{**}	0.1948^{***}	0.0891^{***}	0.0935^{***}

Note: ** and *** = Significant at 95% and 99% confidence levels, respectively.

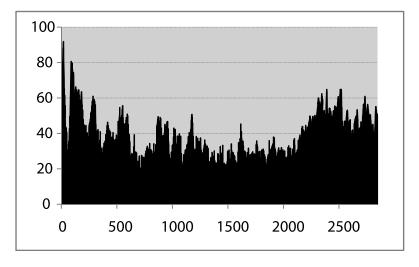
ICt. They also contribute to high percentage shares of ICt in the spread which I will show graphically below.

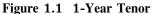
The convergence speed ρ is small, suggesting that it takes dealers quite some time to adjust IC_t gradually until it reaches μ . The longest half life is 12.49 days for 3-year bonds and the shortest is 3.19 days for 15-year bonds.⁶

5.2 Contributions of Asymmetric-Information and Inventory-Control Components in Bid-Ask Spread

The relative importance of AI_t and IC_t in the spread is useful information to the regulators for policy making and market design.⁷ Figures 1.1 to 1.6 show the percentage contributions of AI_t and IC_t to the spread of sample bonds. Consistent with the levels of μ 's in the figures and the average IC components in Table 3, the percentage contributions of ICt are high for 1- and 3-year bonds and they drop to about zero for 5-, 7-, and 10-year bonds. The contributions are highest for 15-year bonds.

Figure 1 Percentage Contributions of Inventory-Control and Asymmetric-Information Components in **Bid-Ask Spread**





⁶ The half life equals $\frac{Ln(0.5)}{Ln(1-\rho)}$

 $^{^{7}}$ The contributions are computed from smoothed AI's. Despite the fact that the μ statistics for certain bonds are not significant, the smoothed AI's are the best estimates for AI's from the noisy BAS data.

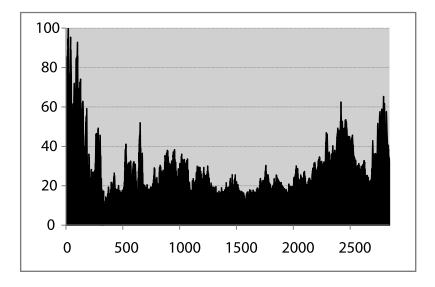
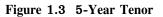
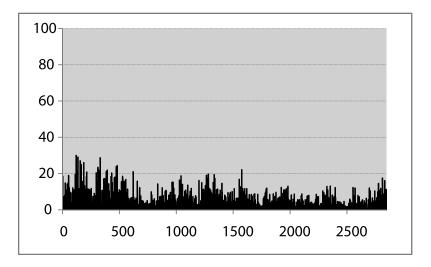


Figure 1.2 3-Year Tenor





^{66...} จุฬาลงกรณ์ธุรกิจปริทัศน์ ปีที่ 37 ฉ.146 ตุลาคม-ธันวาคม 58

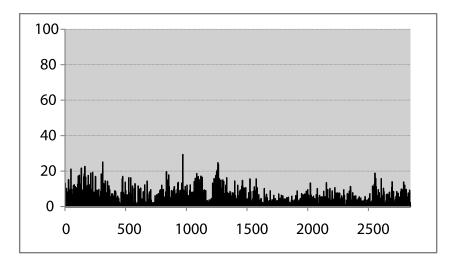
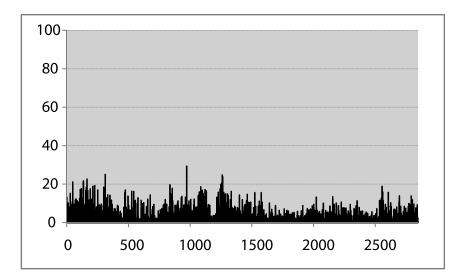


Figure 1.4 7-Year Tenor

Figure 1.5 10-Year Tenor



จุฬาลงกรณ์ธุรกิจปริทัศน์ ปีที่ 37 ฉ.146 ตุลาคม-ธันวาคม 5867

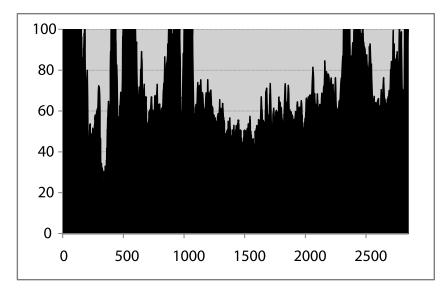


Figure 1.6 15-Year Tenor

Note: The vertical axis is percentage contributions of components and the horizontal axis is day (t) of the sample. The black-shaded area represents inventory-control components, while the grey-shaded area represents asymmetric-information components. Day (t=1) is January 2, 2003 and Day (t=2847) is August 22, 2014.

Given the long sample period, the empirical results may be driven by observations from particular years. For example, the earlier part of the sample is the period following the 1997 financial crisis and it may well be the case that the market was much less active and smaller than it was during the later part of the sample period. To this extent, the bid-ask spread and its components might vary between these two sub-periods. If this is the case the conclusions may be inaccurate.

There are two reasons why inaccurate conclusions should not present in this study. Firstly,

in this study the AI component serves as the state variable. Although the market conditions may as well change randomly over time, the AI component will adjust accordingly to reflect those changing market conditions. Secondly, Table 3 reports the average BAS as well as average AI and IC components in terms of percentage and level for the full sample and for the sub-samples. The first sub-sample is from January 2, 2003 to December 30, 2008, while the second sub-sample is from January 5, 2009 to August 22, 2014. From the table, the averages are not very different for the earlier period from for the later period.

		H	Full Sample	е			Fi	First Sub-sample	nple			Secon	Second Sub-sample	ıple	
	From J.	From January 2, 2003	2, 2003 A	August 22, 2014	2014	From J	anuary 2,	From January 2, 2003 to December 30, 2008	ecember 3	0, 2008	From Ja	nuary 5,	From January 5, 2009 to August 22, 2014	ugust 22.	2014
Tenor	P		C	I	BAS	[¥]	I	CI		BAS	AI			Г	BAS
	%	Level	%	Level	Level	%	Level	%	Level	Level	%	Level	%	Level	Level
1Y	1Y 64.9619 0.0366 35.038	0.0366	_	0.0161	0.0527	0.0527 66.4123 0.0392		33.5877 0.0161	0.0161	0.0553	63.4069 0.0338 36.5931 0.0161	0.0338	36.5931	0.0161	0.0499
3Y	3Y 72.4653 0.1628 27.5347	0.1628		0.0472	0.2100	72.5930	0.1726	27.4070 0.0472	0.0472	0.2198	72.3284	0.1523	27.6716	0.0471	0.1994
5Y	5Y 97.7610 0.3094 2.2390	0.3094		0.0080	0.3174	0.3174 97.2941 0.2999	0.2999	2.7059	0.0097	0.3096	98.2615 0.3196	0.3196	1.7385	0.0062	0.3258
$\gamma \gamma$	7Y 97.8474 0.4924 2.1526	0.4924	2.1526	0.0129	0.5053	97.2806	0.4761	2.7194	0.0164	0.4925	98.4551 0.5100	0.5100	1.5449	0.0091	0.5191
10Y	10Y 97.8485 0.7030 2.1515	0.7030		0.0180	0.7210	0.7210 97.3474 0.6930	0.6930	2.6526	0.0228	0.7158	98.3858 0.7137	0.7137	1.6142	0.0129	0.7266
15Y	28.9004	0.4400	71.0996	0.8172	1.2572	15Y 28.9004 0.4400 71.0996 0.8172 1.2572 27.3209	0.4456	72.6791 0.8018	0.8018	1.2474	1.2474 30.5937 0.4340 69.4063	0.4340	69.4063	0.8337	1.2677

Table 3 Average Asymmetric-Information and Inventory-Control Components in Bid-Ask Spread



5.3 Identification of Informed Traders

For the 5-, 7- and 10-year bonds, the percentage contributions of AI components are very high. So, the high spread must results from those informed traders who trade these bonds in the market. On the one hand, Gravelle (1999) and McGroarty, Gwilyn and Thomas (2007) argued that informed traders were dealers because they could exploit information in clients' order flows for the benefits of their own. On the other hand, however, Foucault et al. (2013) proposed that informed traders could be clients who had superior research and analytical skills and therefore knew better about the true value of bonds. Because informed traders are major contributors to the spread, I also investigate the fundamental issue of who these informed traders are.

To answer this important question, I regress the AI components on outright trading volumes, scaled by the market value, from dealers and clients.⁸ Due to the different sizes of trading volumes among trader groups, the scaled volumes are then normalized by their averages. If traders are informed traders, their trading volumes must be correlated positively with the AI components (Goss, 2008). I obtain the volume and market value data from the Thai Bond Market Association.

Table 4.1 reports the regression coefficients of the AI components on the trading volumes with dealers and with clients. It is found that the relationship for clients is positive and significant for all the tenors. The relationship for dealers is negative or very small. This finding leads me to conclude that informed traders are clients.



⁸ AI components follow a random walk by construction. The regressions are valid only when they are cointegrated regressions. I check for the regression residuals and find that they are stationary. The regressions are cointegrated and the resulting coefficients can be used.

Tenor	Dealer to Dealer	Dealer to Client
1Y	- 4.95E-05	0.0043^{***}
3Y	- 0.0074***	0.0067***
5Y	0.0039*	0.0271^{***}
7Y	0.0005	0.0416***
10Y	- 0.0270***	0.0350^{***}
15Y	0.0019***	0.0951^{***}

Table 4 Identification of Informed Traders

Table 4.1 By Major Counterparties

Note: * and *** = Significant at 90% and 99% confidence levels, respectively. The gray-shaded cells indicate positive and significant statistics.

Table 4.2	By Types	of Clients
-----------	----------	------------

Tenor	Asset Mgt	Insurance	DCO	NDL	FCO	IND	Others
1Y	0.0045^{***}	-0.0028***	0.0036***	-0.0001	-0.0035***	0.0035^{***}	-0.0002
3Y	0.0095^{***}	-0.0145***	0.0109***	-0.0018	-0.0140***	0.0110***	-0.0069***
5Y	0.0274^{***}	-0.0057***	0.0146***	-0.0081***	-0.0060***	0.0150^{***}	-0.0073***
7Y	0.0439^{***}	-0.0055***	0.0241***	-0.0172***	-0.0124***	0.0140***	-0.0122***
10Y	0.0410***	-0.0203***	0.0236***	-0.0079	-0.0243***	0.0160***	-0.0137**
15Y	0.0976^{***}	-0.0153^{*}	0.0572^{***}	-0.0022	-0.0480***	0.0326^{***}	-0.0202*

Note: *, **, and *** = Significant at 90%, 95% and 99% confidence levels, respectively. The gray-shaded cells indicate positive and significant statistics. DCO = domestic companies, NDL = financial institutions with no dealer licenses, FCO = foreign companies and IND = individual investors.

Trading Types	AR(1)		
Dealer to Dealer	-0.6520***		
Dealer to Client	-0.6225***		
Dealer to Asset Management Companies	-0.5994***		
Dealer to Insurance Companies	-0.5559***		
Dealer to DCO	-0.6017***		
Dealer to NDL	-0.4601***		
Dealer to FCO	-0.4871***		
Dealer to IND	-0.5022***		
Dealer to Others	-0.4716***		

Table 4.3 Patterns of Trading Values

Note: *** = Significant at a 99% confidence level. AR(1) is the AR(1) coefficient of the differenced, scaled trading volumes. DCO = domestic companies, NDL = financial institutions with no dealer licenses, FCO = foreign companies and IND = individual investors.

Clients can be asset management companies, insurance companies, domestic companies, foreign companies, financial institutions with no dealer licenses, individual investors and other investors. So some clients may be more or less informed than dealers. In order to examine which particular groups of clients are informed traders, I repeat the procedure for each group. The results are in Table 4.2. I find that the regression coefficients are positive and significant for asset management companies, domestic companies, and individual investors. Based on this finding, I conclude that not all clients are informed. Asset management companies, domestic companies, and individual investors are the only informed clients.

Because the regressors are scaled, normalized trading volumes, the resulting slope coefficients

for client groups can be compared. A high, significantly positive coefficient indicates high market influence of the client group. From Table 4.2, the coefficients for asset management companies are the largest for all except for the 3-year tenor. Based on the sizes of regression coefficients, I conclude that asset management companies are the most influential informed investor group.

In Tables 4.1 and 4.2, I also find negative and significant relationship for certain clients. This relationship implies that dealers adjust the spread downward with the rising trading volume of these clients. To understand this incident, I check for the time series behavior of the trading volumes based on autoregressions of differenced scaled volumes. The results in Table 4.3 show that the volumes are negatively autocorrelated. The AR(1) coefficients are highly significant, implying that order flows of each client group can be predicted. It is not difficult to modify an asymmetric-information model to show that the relationship of AI components with trading volume of poorly informed traders is negative.⁹

6. Discussion

Based on the findings in this study, I conclude for Thailand's bond market that (1) the order-processing costs residing in IC components are very small, (2) the low liquidity of short and long bonds are due to their low floating supply, and (3) clients--especially asset management companies, not dealers are informed traders.

My first conclusion is based on the fact that the order-processing costs must be positive and should be about the same for all bonds. Because the IC components of 5- to 10-year bonds are about zero and the order-processing costs cannot be larger than the IC components, the order-processing costs must be about zero as well.

My second conclusion relies on Gravelle (1999) who suggests that the prices of government bonds are driven by common factors. So the information about all bonds is the same and must be the one on these factors. The small percentage shares of AI components in the spread for short and long bonds cannot result from relatively poorer information of informed traders on these bonds than for the 5- to 10-year bonds. They must come from the large percentage shares of IC components. The inventory control and management of these bonds is risky and costly because of low floating supply of the bonds. For short bonds, the low floating supply is due to the outside option (Gravelle, 1999).¹⁰ For long bonds, the low floating supply is due to their relatively low outstanding value. For example on September 4, 2014, the outstanding value of 10-year-or-shorter loan bonds is 2.22 trillion baht while that of longer-than-10-year bonds is 0.97 trillion baht. Gravelle (1999) notices that low outstanding value translates to low floating supply. Finally, my third conclusion follows Goss (2008) who points out that AI components must rise with trading volume of informed traders.

The findings on the relative importance of AI and IC components have important policy implications and recommendations. The regulators invest tremendous efforts to improve market quality. One way to proceed is to lower bid-ask spread. For 5- to 10-year bonds, the major

⁹ For example in Glosten and Milgrom (1985), provided that the order flow in the last period is not from a noise trader, the dealer revises the noise-trading probability upward in the current period. The resulting bid-ask spread is lower, while it is more likely that the order is coming from a noise trader.

¹⁰The outside option to a bond holder provides two alternatives from which the holder can earn returns from the bond. One is to pay transaction costs and sell the bond in the market. The other is to hold it to maturity and earn coupons plus redemption value.

contributor to bid-ask spread is AI components. A direct approach to lower the spread would be to prevent informed traders from participating in the market. But this approach is not desirable because it prohibits information from flowing into the market via order flows of these traders. The state of being informed is relative to dealers with informed traders. Because bond prices are driven by common factors, there is no private information about the bonds (Gravelle, 1999). The fact that informed traders are being better informed should be interpreted as these traders being equipped with thorough researches and in-depth analyses (Foucault et al., 2013). Dealers in Thailand's bond markets are financial institutions. It should not be difficult for them to lessen their information deficiency. The regulators can help by giving them training and offering them with access to research and databases.

The regulators can reduce the spread for long bonds by the IC-component mechanism. Because the long bonds have low outstanding value that leads to low floating supply, the Public Debt Management Office may consider issuing more long bonds for fund raising in the future.

I have no suggestions to lessen the spread for short bonds. Their spread is already small. Moreover, their outside-option value is naturally high so that investors tend to hold short bonds until their maturities. Finally, the order-processing costs are very low and almost zero. Any attempt to reduce the order-processing costs is a net loss and is not recommended.

7. Conclusion

Bid-ask spread can be decomposed into permanent and transitory components. These components can be related with asymmetricinformation and inventory-control costs being incurred by dealers. Evidence on the relative importance of these components is useful for policy making, market design and market quality improvement. Yet, a study on the subject has never been conducted for Thailand's government bond market.

In this study, I estimate the spread's permanent and transitory components in Thailand's government bond market--using daily bid and ask yields from January 2, 2003 to August 22, 2014. The transitory, inventory-control components exhibit a J-shaped relationship with bond tenors. Their levels and percentage shares fall to almost zero for 5- to 10-year bonds. The asymmetric-information components are correlated positively with dealer-to-client trading volume to which asset management companies contribute most.

These findings have important policy implications and recommendations. Bid-ask spread can be reduced and market liquidity can be enhanced by improving information set, research and analytical skills of dealers and by providing higher floating supply of long bonds. New measures or initiatives to lessen order-processing costs such as new trading or clearing-andsettlement systems are not needed. The orderprocessing costs are already low and almost zero.

References

- Amihud, Y. & Mendelson, H. (1981). Dealership Markets: Market Making with Inventory. Journal of Financial Economics, 8, 31-53.
- Asian Development Bank. (2013) Asia Bond Monitor November 2013. Asian Development Bank. the Philippines.
- Asian Development Bank. (2014). Asia Bond Monitor June 2014, Asian Development Bank. the Philippines.
- Choi, W., Lee, S. & Yu, P. (1998). Estimating the Permanent and Transitory Components of the Bid/Ask Spread. In Lee, C. (Ed.). Advances in Investment Analysis and Portfolio Management 5 (105-122). Connecticut: JAI Press.
- Fleming, M. (2003). Measuring Treasury Market Liquidity. FRBNY Economic Policy Review, 9, 83-108.
- Foucault, T., Pagano, M. & Roell, A. (2013). *Market Liquidity: Theory, Evidence, and Policy.* New York: Oxford University Press.
- Glosten, L. & Harris, L. (1988). Estimating the Components of Bid/Ask Spread, Journal of Financial Economics, 21, 123-142.
- Glosten, L. & Milgrom, P. (1985). Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics*, 14, 71-100.
- Goss, B. (2008). Editor's Introduction. In Goss, B. (Ed.). *Debt, Risk and Liquidity in Futures Markets* (1-17). New York: Routeledge.
- Gravelle, T. (1999). The Market Microstructure of Dealership Equity and Government Securities Markets: How They Differ. Manuscript, Bank of Canada, Ontario.
- Harvey, A. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter.* New York: Cambridge University Press.
- Hasbrouck, J. (1993). Assessing the Quality of a Security Market: A New Approach to Transaction-Cost Measurement. *Review of Financial Studies*, 6, 191-212.
- Ho, T. & Stoll, H. (1981). Optimal Dealer Pricing under Transactions and Return Uncertainty. *Journal of Financial Economics*, 9, 47-73.
- Madhavan, A. & Smidt, S. (1991). A Bayesian Model of Intraday Specialist Pricing. Journal of Financial Economics, 30, 99-134.
- McGroarty, F., Gwilym, O. & Thomas, S. (2007). The Components of Electronic Inter-dealer Spot FX Bid-Ask Spreads. *Journal of Business Finance and Accounting*, 34, 1635-1650.