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Lin, William and Tsai, Shih-Chuan and Sun, David

Tamkang University, Ling Tung University, Taiwan Academy of Banking and Finance

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Price Informativeness and Predictability: How Liquidity Can Help

William T. Lin
Department of Banking and Finance, Tamkang University

Shih-Chuan Tsai[a]
Department of Finance, Ling Tung University

David S. Sun[b]
Taiwan Academy of Banking and Finance

ABSTRACT

Information asymmetry and liquidity concentration has been widely discussed in literatures. This study shows how liquidity influences not only forecasting performances of term structure estimation, but also information transmission and price adjustment across markets. Our analysis helps understanding how extreme market movements affect one another. This study examines, and provides a rationale for incorporating, liquidity in estimating term structure. Forecasting performance can be greatly enhanced when conditioning on trading liquidity. It reduces information asymmetry in the sense of Easley and O'Hara (2004) and Burlacu, Fontaine and Jimenez-Garces (2007). We adopt a time series forecasting model following Diebold and Li (2006) to compare behavior of forecasted price errors. Our findings indicate that forecasted price errors in markets with less depth would influence those with more. Information asymmetry induces volatile trading first and then price adjustment is transmitted to another market due to insufficient market depth. Cross-market price adjustment could be as much as 21 bps on average. Compared with previous studies, our results establish a valid reason to condition on liquidity when forecasting prices.

Keywords: Liquidity; Trading Concentration; Information Asymmetry; Information Transmission; Yield Curve Fitting.
JEL Classification: D82, E43, E47, G12

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[a] Address correspondences to: Shih-Chuan Tsai, Department of Finance, Ling Tung University, 11F-2, No. 18, Sec. 2, Jin-Shan South Road, Taipei, Taiwan, or e-mail: chuant@mail.ltu.edu.tw.

[b] Address correspondences to: David Sun, Taiwan Academy of Banking and Finance, No. 62, Roosevelt Rd., Sec.3, , Taipei, Taiwan 100, or davidsun@mail.tabf.org.tw.

I. Introduction

Information transmission and price adjustment across markets has become more rapid and widespread as global financial market integrates. The disastrous developments of recent international financial markets indicated that substantial price adjustments started in the derivative market where market depth is lower, and other markets followed afterwards. Results from this study suggest that information asymmetry could induce volatile trading followed by price adjustment transmitted to another market for reasons related to market depth. Our analysis in this study helps understanding how market movements affect one another. As liquidity of one market fails to absorb the amount of information contained in extreme price movements, the momentum transferred to another market where liquidity can accommodate further price adjustments. This study provides evidences for price adjustments from markets with less depth to ones with higher depth. Price forecasts conditioned on liquidity prove to be superior to those constructed otherwise. In the analysis of interest rate term structure, our results offer a rationale for incorporating liquidity in curve fitting and price forecasting. Our findings suggest that incorporating liquidity in estimating yield curve and forecasting bond prices could take into account differential information asymmetry across bond markets and thereby produce more reliable estimates and forecasts. Liquidity concentration due to uneven trading activities reflects distinctive levels of information asymmetry in different bond markets, and limitation of market depth induces information dissemination among markets for various bond issues. In particular, the results show that information is transmitted from market with less capacity to those with more, which is consistent with Duarte and Young (2008) in which PIN is priced through market liquidity in addition to information asymmetry. As short term issues are often not traded in a deep market, and are also ideal to be used first to process superior due to shorter horizon, it is reasonable to observe transmission process to start from there. Our analysis suggests that information discovery is improved with proper acknowledgement of market liquidity when forming price forecasts, which justifies the incorporation of liquidity in studying term structure.

There have been ample literatures on the forecasting performance of yield curve fitting in developed government bond markets. Results help determining cost of long term financing arrangements. Trading of government bonds in the less developed markets is, however, characterized by uneven liquidity across maturities, and time since issuance. Although good in-sample fit of yield curves have been well documented, liquidity has not been explicitly considered. Recent literatures on econometrics-based term structure estimation centered on the seminal work of Nelson and Siegel (1987), and subsequently influenced by Dai and Singleton (2003) in their new framework. In terms of out-of-sample forecasting, Diebold-Li (2006) employed factorization by modeling the factors as simple time series processes, while Favero, Niu and Sala (2007) applied an affine model for term structure forecasting in their factor processes. Liquidity is however not incorporated in this dynamic setting. As implied yields of benchmark on-the-run issues often carry a liquidity premium caused by trading concentration, it leads to biases in the estimated term structure. Without considering this fact could result in distortion of implied spot rates and factors driving long-run term structure may be overlooked as well. However, theoretic and empirical attention to liquidity premium in bond markets is well documented. Duffie, Garleanu and Pedersen (2005) proposed a general theoretical model for liquidity premium in an OTC market. Vayanos and Wang (2007) argued that the liquidity premium would be more substantial in markets where trading concentrates. Empirically, Amihud and Mendelson (1991) analyzed how liquidity affects Treasury bill yields. Warga (1992) suggested that liquidity is priced such that on-the-run issues have lower returns than off-the-run ones. Elton and Green (1998) also considered trading volume as a proxy for liquidity. There are evidences from the international markets as well. Eom, Subramanyam and Uno (2002) studied liquidity effects in the Japanese market, while Diaz, Merrick and Navarro (2006) in the Spanish government bond market. Their results indicated that it is crucial, especially in the emerging markets, to control liquidity concentration effect while estimating yield curve.

Recent studies[3] have noted the importance of relative liquidities of government bonds. Liquidity premia have been documented on yields of illiquid bonds. Especially in an emerging bond market where trading concentration is substantial[4], liquidity attached to the more or the most liquid issue is persistently and significantly higher than others. There are also literatures on information and security returns in various areas. Studies on information risk in government securities such as Brandt and Kavajecz (2004) and Green (2004) related trading liquidity to information risks. Easley, Hvidkjaer and O'Hara (2002) found that stocks with more private information and less public information tend to have a higher excess return, which can serve as a proxy for information asymmetry. The advantage of informed traders creates risks for uninformed traders, so an information risk premium is required for the uninformed to enter a transaction. This information risk premium has also been supported by Burlacu, Fontaine and Jimenez-Garces (2007). Easley and O'Hara (2004) have derived from excess returns caused by information asymmetry a measure called Probability of Informed Trading (PIN).

[3] Liquidity in the Treasury markets has been the topic of numerous studies. See for example, Sarig and Warga (1989), Amihud and Mendelson (1991), Warga (1992), Daves and Ehrhardt (1993), Kamara (1994), Elton and Green (1998), Fleming (2002, 2003), Strebulaev (2002), Krishnamurthy (2002) and Goldreich, Hanke and Nath (2005).

[4] See Darbha (2004) and Diaz, *et al.* (2006), among others.

Duarte and Young (2008) argued, however, that PIN should be priced to reflect both information asymmetry and illiquidity in a market. Datta and Datta (1996) suggested that the absence of any reporting requirement for insider bond transactions may create an enhanced opportunity for insiders to exploit private information to expropriate wealth from uninformed bond traders. Zhou (2007) argued that bond traders who possess superior information about certain issues might take advantage of this private information at the expense of uninformed traders and therefore a compensation for bearing the asymmetric information risk is required for the uninformed to participate in the trade. Goyenko, Subrahmanyam and Ukhov (2008) noted that spreads of high-yield corporate bonds are significantly affected by the degree of information asymmetry using a transaction-based Asymmetric Information Measure (AIM) for individual corporate bonds[5].

In terms of estimation method in dealing with liquidity, the following works are helpful in leading us to the methods we have adopted in this study. The control of liquidity effect can be carried out in several ways. Bolder and Sterilski (1997) used a subset of bonds based on liquidity and estimate the yield curve on the selected issues. Estimating such a 'liquid yield curve' may just omit issues of very long and short maturities in an emerging market due to their low liquidity. Elton and Green (1998) and Alonso, Blanco, del Rio and Sanchis (2004) estimated yield curve jointly with a liquidity function to cover the effect of non-interest rate factors, which could be affected the nonnegative nature of the liquidity effects. Lastly, the approach of Subramanian (2001) and Dutta, Basu and Vaidyanathan (2005) employ a weighting scheme based on one or more liquidity proxies to estimate yield curve by minimizing weighted pricing errors. Impacts from more liquid issues are weighted or penalized more in the optimization, so the resulting yield curve estimated is always closer to the observed yields of the more liquid issues. It is found, however, in Lin and Sun (2007) that pricing errors generated from the liquidity-weighted yield curve model are systematically related to idiosyncratic rather than systematic factors.

In this study, we intend to identify rationales for incorporating liquidity in term structure fitting and how it improves forecasting performance. Short-horizon out-of-sample forecasting errors between unweighted and liquidity-weighted fitting models are compared. In terms of forecasting performances, the liquidity-weighted method proves to be better in accuracy as indicated by mean absolute error, and also in consistency judging from the variance of forecasting errors. Among literatures on forecasting term structure, Dolan (1999) first suggested empirically that the curvature factor, or β_2 in Nelson and

[5] The AIM measure is obtained directly from a Rational Expectations (RE) model with multiple securities and many sources of uncertainty. This model is essentially a generalization of the Grossman and Stiglitz (1980) model, which focuses

Siegel (1987), can be used to forecast future yields. Diebod and Li (2007) made thorough comparisons among various time series forecasting models for term structure. Reisman and Zohar (2004) have used a factor model in fitting and then modeled the two leading factors with an ARIMA process. As our method focuses more on uneven liquidity across various issues, our results it suggests specifically that information asymmetry is lower in a more liquid market. Our liquidity-based weighting adopts a scheme similar to those in Subramanian (2001) and Dutta *et al.* (2005). Our results address forecasting errors over various short-run windows and are therefore important for portfolio management, derivatives pricing and risk management in the short run. Using AIM as a gauge of the informational content of trading liquidity, we demonstrate that liquidity reduces informational asymmetry in a market, a result consistent with the model of Vayanos and Wang (2007). Furthermore, we also find that markets for the less liquid and off-the-run government bonds exhibit higher AIM in general, which confirms findings of Goyenko, *et al*. (2008). Fitting term structure while conditioning on liquidity enhances forecasting performance and reduces information asymmetry. It also enhances information flow from markets with less depth to the deeper markets, and contributes to the efficient absorption of information asymmetry by prices through trading process. In terms of yield, cross-market price adjustment could be as much as 21 bps on average. In our study, short term and very long term issues are often the ones with lower market depth. But the markets for short term issues are also ideal to be used first to capitalize gains from superior information as pricing noise is smaller due to shorter horizon. Our results may help characterizing developments of recent international financial turmoil where price adjustments started from derivative markets with less depth and then passed over to the deeper bond, stock and currency markets across the world.

Our study has several contributions to the practice of fixed income security markets. First, we provide a rationale for applying liquidity adjustment in the estimation of term structure, especially in the emerging markets. Other than technical reasons, it reduces informational asymmetry and helps capturing price premium statically as well as dynamically. Second, our forecasting approach provides a mechanism consistent with regularities in observed market phenomenon in exploring information discovery based on knowledge of market liquidity. The rest of the paper is organized as follows. In Section 2 we provide a detailed description of a modeling framework with our definition of liquidity weighting scheme. Section 3 reports our data and preliminary estimation results. In section 4 we conduct further investigation on how information and price adjustment transmits among markets. Section 5 gives concluding remarks.

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on an economy where some investors are more informed on the future distributions of a security's returns than others.

II. Liquidity, Information and Term Structure

Trading of government bonds in the emerging markets has been characterized by limited number of issues on the one hand and liquidity concentration on the other. Empirical examination of trading concentration and related security returns can be found in literatures that follow. Darbha (2004) addressed this issue on the Indian government bond market, where trading is concentrated more on medium maturity issues. Alonso, *et al*. (2004) studied the Spanish Treasury bond market and found significant liquidity premia in off-the-run issues, where the average number of issues in their estimation is 38. Diaz, *et al*. (2006) also studied the same bond market and indicated specifically that the 10-year on-the-run issue accounted for as much as 23.5% of the total market volume in the period of 1998-2002. The average number of concurrently outstanding issues is only around 30. Although liquidity concentration phenomenon is not pronounced in the more developed market, Shen and Starr (1998) have studied a liquidity-based term structure model for T-bills. Amihud and Mendleson (1991) have argued that more liquid issues are traded with lower yield. Longstaff (2004) has also demonstrated that the liquidity premium could be as high as 15%. Elton and Green (1998) used volume as a proxy for liquidity and found significant results in explaining US zero-coupon yields. Shen and Starr (1998) used monthly and quarterly bid-ask spreads to analyze term premium between 6-month and 3-month US T-bills. We will extend the model of Elton and Green (1998) and Burlacu, Fontaine and Jimenez-Garces (2007) by using trading liquidity as the conditioning variable to demonstrate how liquidity affects the estimation of term structure. Our analysis supports the incorporation of liquidity primarily because better information dissemination would be achieved.

Taiwan's government bond market has reached, on the outright transactions, an average daily trading volume of around 13 billion US dollars with a total of 67 outstanding issues between 2005 and 2007, which is about 48% of the Canadian government bond market volume, 2.7% of the US treasury volume and 4.3% of the Japanese government bond trading volume. A repo market is also active with an average daily volume of around 8.5 billion dollars during the same period. Trading primarily takes place in a centralized matching market, the Electronic Bond Trading System (EBTS). Over-the-counter trading is still in place, where 13 of the 87 dealers are primary dealers, but accounts only for about 8 percent of the total volume during 2006. Repos are, however, still mainly traded over the counter through dealers. Contract terms of repos concentrate from overnight up to 30 days. Special repos are only available on the EBTS for overnight contracts, accounting for about 10 percent of the total repo volume, and hence around 4 percent of the total government bond volume. Both outright and special repo trading is extremely concentrated in the on-the-run, especially the 10-year, issues which normally constitutes more than two thirds of the daily trading volume. With this drastic concentration of liquidity, it is reasonable to incorporate the effect of liquidity when estimating the sport rate term structure for the Taiwan market. Although some consideration of liquidity measures has been noted in various literatures about this market, it has not been incorporated in the yield curve fitting process. The fact that the special repos are almost entirely on the same 10-year issue could be a major factor to the concentration in the outright market in the sense of Duffie, *et al*. (2005). Yuan (2005) suggested that information effect of benchmark issues due to systematic variable other than interest rates could be analyzed with a liquidity-weighting yield curve fitting. Information about systematic and idiosyncratic risks can be extracted from the trading of benchmark security. In a market of asymmetric information, Yuan (2005) suggested that over time the liquidity-related changes will affect subsequent trading among markets. This intertemporal relation is a major part of our analysis. Forecasted price errors in one period help predicting errors in the next period. Instead of considering liquidity-related premium in the context of a single period, our study that follows will examine fitting results along the evolution of trading in major government bond issues.

Liquidity and asymmetric information in government bond markets

Burlacu, *et al*. (2007) extended the model of Grossman and Stiglitz (1980) and proposed the following definition of AIM,

$$AIM^{i} = 1 - \frac{Var(P_1^i - P_0^i \mid P_0)}{Var(P_1^i - P_0^i)} \tag{1}$$

where P_0^i denotes the price of *i*th security at time 0 and P_1^i is its price at time 1. P_0 is a vector of prices for all the security, which has with nontrivial correlations with the *i*th security. Intuitively, if information about this security is asymmetrically allocated in the market, price of a security would contain some private information about future returns. If private information is not revealed by prices, then it is related to future returns. The AIM measure in (1) uses the degree of correlation between current security prices and future returns as a measure of the private information contained in the price of security. Burlacu, *et al*. (2007) utilize this measure in a regression where the AIM measure is obtained by projecting one-period bond price change on price level at the beginning of the corresponding period. The resulting R^2 from the regression is equivalent to the AIM under a rational expectations model. In a market where information about security *i* is allocated in a symmetric way, relative liquidity contains no further information about future price movements. As a result, current relative liquidity is not correlated with any future price changes, and hence is not useful in reducing associated uncertainties, which amounts to

$$Var(P_1^i - P_0^i \mid P_0) = Var(P_1^i - P_0^i)$$

and

$$AIM^i = 0.$$

In a market with information asymmetry, part of the information about future price movements is kept by the informed traders and not released until the realization of future price. Future security price changes will depend on current price levels which help reducing uncertainties about future price changes

$$Var(P_1^i - P_0^i \mid P_0) < Var(P_1^i - P_0^i)$$

and

$$AIM^i > 0$$

The degree of dependence of future price changes on current price levels serves as a valuable measure of the amount of private information embedded in trading liquidities. The more private information retained by the informed traders, the smaller the conditional variance of future price changes and the higher the difference between $Var(P_1^i - P_0^i)$ and $Var(P_1^i - P_0^i \mid P_0)$, hence the higher AIM^i is.

Instead of (1), we propose alternatively another measure as

$$AIM^a = 1 - \frac{Var(P_1 - P_{0,1}^f \mid V_0)}{Var(P_1 - P_{0,1}^f)} \tag{2}$$

where V_0 denotes the relative trading volume of the security. $P_{0,1}^f$ is a forecast of P_1 formed in period 0 and is a function of P_0. In our case, government bonds are the group of securities of interest. Instead of conditioning V_0 in a linear regression, we incorporate it in a nonlinear optimization. So the spirit is similar to that of Burlacu, *et al*. (2007) except that our conditioning process is more implicit. This version of AIM^a will be obtained through the computation of variance of a series of forecasted price errors rather than from a single regression. Its implication on gauging information asymmetry remains without loss of generality.

Liquidity-adjusted term structure fitting

To determine the information effect contained in a benchmark government bond, we need to compare yields on issues with different market liquidity. According to Brandt and Kavajecz (2004), part of the extra yields on the less liquid issues is to compensate for the lack of price informativeness; therefore term structure fitted without a liquidity component would have left out the information effect. Based on this consideration, we will try to fit a liquidity-adjusted term structure and examine related information effect over time. In fitting the Taiwan term structure we follow the works of Subramanian (2001) and Vaidyanathan, Dutta and Basu (2005) with a liquidity-weighted optimization process. Two weighting schemes have been constructed initially to contrast the unweighted fitting model. One depends on liquidity only, while the other utilizes both liquidity and duration to examine the validity of liquidity effect. However, only the results based on the first scheme are reported since the difference between the two is marginal but the first one is more appropriate for information related analysis.

As for the fitting model, we use the four-factor model from Svensson (1994), or the Nelson-Siegel-Svensson (NSS) model to estimate parameters of spot rate function, which is

$$R(t) = \beta_0 + \beta_1 \times \left[\frac{1-\exp(\frac{-m}{\tau_1})}{\frac{-m}{\tau_1}} \right] + \beta_2 \times \left[\frac{1-\exp(\frac{-m}{\tau_1})}{\frac{-m}{\tau_1}} - \exp(\frac{-m}{\tau_1}) \right] + \beta_3 \times \left[\frac{1-\exp(\frac{-m}{\tau_2})}{\frac{-m}{\tau_2}} - \exp(\frac{-m}{\tau_2}) \right] \tag{3}$$

where β_0, β_1 β_2 and β_3 are the parameters to be fitted. Fitted government bond prices are obtained from a valuation equation and applied on data in the sample period, with and without being weighted by trading liquidity. Optimization with a squared error criterion tends to amplify pricing errors since larger error terms of less liquid issues would contribute more to the objective function than to those of the more liquid ones. We then adopted an objective function minimizing the sum of weighted absolute deviations to reduce noises caused by uneven liquidity distribution.

$$\min[\xi(\theta)] = \min\left[\sum_{i=1}^{n} w_i \left| B_i - \hat{B}_i \right| \right] \tag{4}$$

where B_i and $\hat{B}_i$ are actual and fitted bond prices respectively. Following Elton and Green (1998) and

Dutta, Basu and Vaidyanathan (2005), we defined weights w_i in (4) by

$$W_i = V_i^{1/2} \tag{5}$$

and

$$w_i = \frac{W_i}{\sum W_i} \tag{6}$$

where V_i is the daily trading volume of security i respectively, which we use here as the proxy for liquidity[6]. The raw weight W_i is constructed proportional to the squared root of V_i to reduce the unevenness in weight distribution and avoid excessive distortion in fitting results caused by that. Subramanian (2001) used a hyperbolic tangent function in building a weighting scheme,

$$W_i = \tanh\left(\frac{-V_i}{V_{\max}}\right) + \tanh\left(\frac{-n_i}{n_{\max}}\right) \tag{7}$$

where V_i and n_i are daily trading volume and number of trades of the respective security on the given day respectively, while V_{max} and n_{max} are the maximum volume and number of trades among all the securities traded on that day. This scheme would, however, produce weights falling fast as liquidity decreases, and therefore is not an ideal choice for the Taiwan market.

For the four parameters in (3), we extend the idea of Diebold and Li (2006) to fit an ARMA model for each of the four according to Akaike information criteria and Durbin-Watson statistics. The time series model is done on a walk-forward way (5, 10, 20 and 30 days ahead) starting from the issuing day of the bond. Projected parameters are substituted into the spot rate function in (3) to compute a forecasted price. Forecast error is the difference between the actual and forecasted price as

$$\varepsilon_{i,t+h} = P_{i,t+h} - \hat{P}_{i,t+h} \tag{8}$$

where h is the walk-forward window (5, 10, 20 or 30 days). We denote $\{\varepsilon_{i,t}\}_{t=1}^{N}$ and $\{\varepsilon_{j,t}\}_{t=1}^{N}$ as forecast errors respectively for unweighted and liquidity-weighted fitting schemes. For each series we

[6] We have used alternative liquidity measures such as the inverse of average bid-ask spreads and average number of quotes or trades. Fitted results are not much different from using trading volume as the proxy for liquidity. But using trading volume as the proxy produces the best performance in consistency and accuracy, especially in periods of extremely uneven

compute their average by a measure called Mean Absolute Error (MAE), which is defined as

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|\varepsilon_{it}\right| \tag{9}$$

to gauge the accuracy achieved by each series. We also compute variances of both series to compare difference in consistency between them. The difference between the two series

$$d_t = |\varepsilon_{i,t}| - |\varepsilon_{j,t}| \tag{10}$$

is then used to test if, for each bond, the difference between unweighted and weighted forecast errors is significant. For that purpose a *t*-statistic is constructed as

$$t = \frac{d_t}{S_d / \sqrt{N}},$$

where d_t follows (9) and

$$S_d = \sqrt{\frac{\sum_{t=1}^{n}(d_t - \overline{d})}{N-1}},$$

and

$$\overline{d} = \frac{\sum_{t=1}^{N} d_t}{N}.$$

distribution of liquidity across markets for various issues.

III. Data and Results

Our data is obtained from the EBTS of Gretai Securities Market in Taipei from January 1, 2003 to December 31, 2006. The data contains transaction prices of all the records submitted through EBTS. Closing prices are selected for each issue whenever there is nonzero trading volume. To avoid non-trading problem we have excluded also days without any bid and ask records. For the validity and stability of the sample, prices of the 30-year issues and when-issue data are also excluded. So our term structure fits only up to 20 years the spot rates of the Taiwan market. There are altogether 68 issues with valid trading data during this period. We have compiled data for a total of 994 days with a reasonable number of issues traded in each day. The numbers of issues are between 18 to 35 in each given day, with an average of around 22 through out the whole period. The number of transaction price for the 2- and 5-year issues ranges from 5 to 20 in a given day, depending on days from issuance. For the heavily traded 10-year issue, the number could be as large as 400 when the issue is on the run. So the market depth of short-term issue is quite low relative to that of the 10-year issue. We will employ those issued before 2006 as in-sample data set to calibrate our forecast models and the prices of ones issued in 2006 as out-of-sample set for the comparison of forecasting performances.

Two schemes of weight construction are used to produce weights, which are averaged over all the days where trading prices are available, or separately over the first 30 trading days. The first scheme follows (5) and is proportional to the squared root of trading volume. For the purpose of robustness, we have also added a second scheme with duration as a supplemental weighting factor beside liquidity. The second scheme adds the duration of the respective issue to the raw weight defined in (5). Table 1 shows that the weight distribution across issues is quite uneven. As trading is more active for a specific issue while it is on the run, the average weights for the entire trading period of each issue are in general smaller than those during initial trading days. Adding duration in the weight construction greatly reduces the unevenness of weight distribution. Within the first set of weights, the 10-year issues can account for up to an average of around 65 percent in the first trading 30 days from issuance and still around 20 percent in the extended trading period after that. Weights for the 5- and 2-year issues are generally only one-sixth those of the 10-year ones, with weights for 5-year ones slightly larger. On the second weighting scheme, weight for any single 10-year issue accounts for only up to 15 percent in the first 30 days and down to an average of about 7 percent in the long run. The effect of adding in duration in the weight construction is, however, not significant on 5- and 2-year issues. It is obvious that the inclusion of duration has reduced the liquidity adjustment effect substantially.

On-the-run issues are the ones with trading concentrates. Normally for the 2-year bonds, on-the-run issue is the only one with trading activity. For the more active 5-, 10- and 20-year bonds, on-the-run issues generally account for over half of the trading volume at all times. In order to extract potential information related effects from the fitting process, we will have to focus on a weighting scheme based on liquidity only, despite that the addition of duration may lessen distortions caused by heavily uneven liquidity distribution. Lin and Sun (2007) has compared difference between results from two weighting schemes and it is shown that adding duration in weight construction helps in terms of information related analysis only marginally. Considering that, we will only adopt a liquidity-only weighting scheme in our fitting algorithm.

In a separate analysis not reported here, we have compared the performance between the NSS model against another popular B-Spline model, with and without liquidity weighting. Generally speaking, for unweighted fitting NSS is smoother than the B-Spline method as seen in other studies. B-Spline model would exhibit more oscillation, which is related to the fact that the on-the-run 10-year issue was traded at a dominant volume. So the weighted yield curve has a dip on the 10-year maturity. The weighted curve is lower than the unweighted one at 10-year by an average of about 10 b.p., which causes two humps from optimization under the B-Spline model. The NSS model, however, provides a more moderate curvature. Dutta, Basu and Vaidyanathan (2005) concluded that the NSS model with liquidity adjustment is the most stable fitting method. However, as argued in Bliss (1997), the length of fitting period seems to affect the comparison of performance among models. It was found that the Smoothed Fama-Bliss method performs better in the short run, while the McCulloch Cubic Spline works better in the long run. To the extent that the combination of issues of various long and short term influences fitting result, our findings exemplifies a working model appropriate for long term issues.

Analyzing forecasting performance of term structure is the basic idea of Diebold and Li (2006), which adopted the NSS model and showed that the three coefficients of the yield curve function may be interpreted as latent level, slope and curvature factors. In this study we include all of the four coefficients in (3), and our focus is on how the forecasting performance is enhanced conditioning on trading liquidity, which is the first key difference. Our model differs from Diebold and Li (2006) also in that the comparison we make among issues of various terms discloses how liquidity conveys information differently among markets for issues with different maturity terms. Specifically we demonstrate that the effect of liquidity is more pronounced in the more concentrated markets for on-the-run 10- and 5-year issues. Lack of liquidity in off-the-run issues and all the 2- and 20-year issues induces higher level of information asymmetry. This is consistent with the observation of Goyenko, Subrahmanyam and Ukhov (2008). We compare results from the liquidity-weighted model with those from the unweighted one. Each day we apply the NSS model to obtain four parameters, derived from transaction prices, liquidity and cash flow applicable on that day. Forecasted price for the next day is computed by applying parameter on that day to the cash flow array applicable on the next day. One-day-ahead forecast errors are then computed by subtracting the forecast price from actual traded price each day. This measure is employed in our study in place of the commonly used RMSE measure. From a practical perspective, the forecasted price errors tell how a fitting scheme performs in a trading environment. If we can tell how well market participants can infer from the forecasted error series, we would be more confident to use the scheme in a practical sense.

As a preliminary analysis, for each issue we construct one-day-ahead forecasted price errors only for the first three trading months. Table 2 reports the summary statistics for a preliminary analysis on the in-sample data. For the most liquid 10-year issues, forecast price errors tend to be negative across the board, a natural subsequence of fitted higher price (lower yield) than the less liquid 5- and 2-year issues. A liquidity-weighted model generates even more upward-adjusted forecast prices, hence more negative forecasted errors. For the 5-year issues errors are less so following the pattern, while those for the 2- and 20-year ones even exhibit positive forecasted errors, reflecting suppressed forecasted prices. Also, the liquidity-weighted forecast price errors, especially on the 10-year issues, have larger standard deviation than the unweighted ones, a result of being optimized on absolute deviations. More recent issues tend to have smaller standard deviations. For the less liquid 2- and 5- and 20-year issues, the difference is less pronounced and standard deviations are also smaller. However, forecasted errors for the relative more liquid 5-year issues tend to be larger from the liquidity-weighted fitting process than from the unweighted one. But for the least liquid 2- and 20-year issues, forecasted errors are actually raised due to the fact that their prices are compressed for lack of informational content. Lin and Sun (2007) studied the relations among forecast errors from various issues and presented evidences on how trading liquidity coveys information about term structure. We can see in Table 2 that liquidity-weighted term structure fitting exhibits a similar information effect. Higher prices than in the unweighted fitting are forecasted for the more liquid 5- and 10-year issues to reflect the information contained in their higher market liquidity. As fitted model parameters change every day, results in Table 2 cannot be used to compare forecasting performance over an extended period. Besides, if informational contained in prices are not fully released in one day, then a measurement on information dissemination over time needs to be considered.

To obtain extended price forecasts, we have adopted a time series scheme similar to that of

Diebold and Li (2006). Prices are forecasted using projected NSS parameters applied back to the NSS pricing model. Daily NSS estimation is done for the entire data set, but only parameters in the estimation period (2003 to 2005) are used in the ARIMA estimations independently for each term. The estimation results for these parameters are reported in Table 3. Orders of the models are selected according to the Schwartz Bayesian Criterion (SBC). In general, parameters fitted from liquidity-weighted model carry higher orders of autoregression. We then apply the projection models during the forecasting period of 2006 respectively on each of the four NSS parameters, and separately for unweighted and liquidity-weighted schemes to obtain forecasted parameters 5, 10, 20 and 30 days ahead. Integrating the projected NSS parameters and cash flow data for the forecasting day we can derive the forecasted prices. Forecasted errors are then computed from the difference between observed prices and forecasted prices on each given day. The same process is carried out for 5- 10-, 20-, and 30-day forward windows. Table 4 gives results for the 2-year issue, A95104. To present our analysis effectively, we have used three separate measures. The first one is the MAE of forecasted price errors to report the accuracy of our forecasts. To demonstrate consistency of our method, we have also adopted a second indicator, variance of forecasted price errors. Thirdly, to distinguish the effectiveness of liquidity weighting and its information effect across terms and over different forecasting windows, we have also presented AIM^{a}, according to (2), for each forecast.

Regardless of forecasting windows, the MAE's and variances from the liquidity-weighted method are uniformly lower than those from the unweighted method, suggesting that the former method produces more accurate and consistent forecasts. The *t*-statistic for the comparison between the two methods is also significant for all forecasting windows. To reduce trading noises due to low liquidity during the period when the issue becomes an off-the-run issue, we have also recomputed the results for just the first three months when the issue is still on the run. The results show that MAE and variance are smaller across the board as we expected. The *t*-statistics are also more significant in the on-the-run period. A more revealing result is that the distribution of AIM^{a} shows that it not only drops as forecast is made in more extended windows; it is also lower when the respective issue is traded on the run. If it is the case that an informed trader's information superiority over that of an uninformed falls with longer forecasting horizon then information asymmetry would be less severe when making more extended forecasts. On the other hand, when the issue is on the run, more information is exchanged through trading and therefore information asymmetry is also less pronounced. Similar patterns appear for the 5- and 10-year issues as seen in Tables 5 and 6. MAE, variance and *t*-statistic are all indicating that liquidity-weighting improves forecasting results substantially. On-the-run period performs generally better than the entire sample period across all issue at given terms. As for the results of AIM, there are more dimensions in Table 5 and 6 where there are results for two issues. For each issue there is one analysis covering the entire period where data is available, as well as the analysis for only the on-the-run period. Even for the unweighted forecasts, AIM's are lower for the on-the-run issue, confirming the necessity of our approach in separating out an on-the-run period for each issue from the entire period. It is also crucial to note that comparisons across the four terms suggest that AIM is in general higher for the less liquid 2-year issue, and lower for the more liquid 5- and 10-year ones. Consistent with Goyenko, Subrahmanyam and Ukhov (2008), this phenomenon suggests that information asymmetry is more severe in the short-term, less liquid or off-the-run markets. Conditioning on trading liquidity, information asymmetry reduces uniformly, an indication that liquidity carries valuable market information. From the perspective of trading, forecasts conditioned on trading liquidity can perform much better than otherwise. As an issue becomes off the run, the information effect diminishes. Our work is then in the very spirit of Goldreich *et al.* (2005) and consistent with Alonso, *et al*. (2004).

To the extent that implied information asymmetry falls with higher liquidity, our argument is that using trading liquidity as a reference market participants are utilizing rationally all possible information. Forecasts are therefore made with more accuracy and consistency, and can help the uninformed to execute subsequent trades under informationally less inferior terms. The fact that information asymmetry is lower in a market for on-the-run issues comes from the trading concentration and information dissemination mechanism modeled in Vayanos and Wang (2007). In the government bond markets where issues take turn going from on-the-run to off-the-run, the argument of information asymmetry appears to be especially interesting as trading concentration varies across issues and, for each issue, over time. In estimating interest rate term structure, the incorporation of liquidity helps pricing cost resulted from information asymmetry. Literatures on the evolution of adverse selection costs have addressed the issue of long memory and its implication. The gradual decrease of AIM in our study is consistent with the long memory hypothesis in explaining the evolution of information asymmetry in the market for a specific bond issue. On the other hand, the effect of liquidity on information asymmetry across different issues is compatible with findings of Henker and Wang (2006) which documented a negative relationship between volume and adverse selection costs.

IV. Information Transmission causes price adjustments across Markets

We have argued in the previous sections that liquidity in a government bond market conveys information and therefore reduces informational asymmetry. It is also shown that the degree of informational asymmetry differs across issues. In this section, we will extend findings from the preceding sections and examine if, and how, the reduction of informational asymmetry carries from one market to another within a given period. This examination of how AIM's evolve among various markets in our data set helps further clarifying the price effects of liquidity. Specifically, evidences presented in this section supports the notion that reduction of informational asymmetry is achieved through price adjustments starting from the short-term or off-the-run issues due to market depth in the respective markets, and then moving to other issues accordingly.

Table 7 reports the results of a Vector Autoregression (VAR) analysis on forecasted price errors, through unweighted and liquidity-weighted fitting, in the forecasting period of 2006. This analysis attempts to identify causations among price errors of various issues that contribute to the patterns of AIM's as reported in Tables 4 through 6. Specifically we have considered a regression as follows,

$$FE_t^j = \beta_0 + \sum_{i=1}^{n}\sum_{k=1}^{l}\beta_{ik}FE_{t-k} + \varepsilon_{jt},\ j = 1, 2...n, \tag{11}$$

where FE_t^j is the obtained by subtracting the one-day-ahead forecasted price of bond *j* on a given day from its closing price of the same day. We have used one-day-ahead forecasted price errors in (11) instead of the more extended forecasting results employed in the last section to minimize loss of degrees of freedom. Note that we have examined distribution of similar forecast errors in the estimation period (before 2006). To provide more detailed results in supporting findings from the last section, we need to employ the similar measures specifically in the forecasting period of 2006. The VAR estimation was carried out separately in four periods. Within each period we use only issues traded concurrently to identify potential causation among forecast errors of various issues. So the numbers of observations are small in general. But the results are consistent with one another across the four separate periods. Although lags are of different orders, coefficients in general tend to be significant for either the own lag terms, or for lags of an issue of shorter term which has been traded for an extended period of time.

For the *liquidity-weighted* forecasted errors, except in the second panel where the 10-year on-the-run issue is the dependent variable, or when regressed as an own lag term, errors of the 20-year issue are never significant as an independent variable. Coefficients for issues of the shorter term or away from initial issuing day tend to be more significant through out the periods. Whenever there are two issues concurrently traded in the same period, the off-the-run one tend to be more influential. Cases of A95103 and A95102 in the last two periods exemplify this pattern. The 2- and 5-year issues, when their lag errors are regressed on, are the ones with the most occurrences of significant coefficients in all periods, except when the respective issue just starts trading in the given period. The most liquid 10-year issues are only significant when regressed on as their own lag terms. Translated into magnitudes of yields, results in panel (d) of Table 7 and those in Table 2 suggest that forecast price errors of a 2-year issue (A95104) on average contribute around 14 bps to the forecast errors of a 5-year on-the-run issue (A95105) during that period. In the meantime, forecast price errors of a 5-year off-the-run issue (A95101) on average contribute around 7 bps to the forecast errors of a 10-year on-the-run issue (A95106). However, an off-the-run 10-year issue (A95105) alone could contribute up to 40 bps. In the case of the *unweighted* errors, most of the effects across issues disappear. Only autocorrelation coefficients are significant in the VAR estimation. This result suggests that, if *not* conditioned on liquidity, forecasted errors realized in market with little depth cannot be used to make profits in capturing forecasted price errors in another market. In this sense, liquidity-based term structure estimation is more superior in providing day to day trading signals for arbitrage profits.

The original AIM definition of Burlacu, *et al.* (2007), as shown in (1), is adopted in Table 7 with a minor modification to further clarify how possible information could have been transferred among markets for various issues. The R^2 of a regression like (11) is proportional to the AIM defined by Burlacu, *et al.* (2007) as FE_t^j is a monotonic transformation of price change of bond *j* from periods 0 to 1. We have given it an alternative term called AIM^b to be differentiated from AIM^a used in the previous section. There is a difference between the interpretations of two measures. AIM^a focuses on the distributions of forecasted errors within a given window, so it measures the *remaining* information asymmetry after utilizing, or not utilizing, liquidity to condition price forecasts. Alternatively AIM^b, as a function proportional to R^2, gauges how much the information asymmetry in the specific market is *expected* to be reduced in the conditioning process. Therefore, in the previous section, lower AIM^a for a more liquid issue suggests that there is less information asymmetry which remains. As we extend the forecast windows, an informed trader's information superiority falls and the remaining information asymmetry decreases. However, in this section AIM^b reflects the correlation of conditioning forecasted errors with the conditioned ones. The higher AIM^b is the more information will be reduced in the process.

Within each given period, when off-the-run issues, or those with lower market depth such as the 2-, 5- or 20-year issues, modeled as dependent variables, regressions tend to produce lower AIM's. AIM's are in general higher when forecast errors of more liquid or on-the-run issues are regressed on lagged terms of forecast errors of less liquid or off-the-run issues. This signifies that more information is conveyed in the respective process. Although this version of AIM rises with the increase of dependent variables, the VAR model at each given period ensures the comparisons of AIM's to be free of that issue. So the AIM analysis in Table 7 suggests that more information is revealed through price adjustments due to surprise arising from bond markets with little market depth, but not the other way around. Again this phenomenon is more pronounced for liquidity-weighted forecast errors. The VAR estimation based on unweighted forecast errors in general reveals that little information is conveyed even after considering forecast errors from other issues. The market for 2-year issues often has relatively lower market depth and is where profiting from superior information is potentially easier than other market as pricing noise is smaller due to shorter horizon. So it is reasonable to observe liquidity-induced information transmission and price adjustment to start from the 2-year issues.

The evidence above indicates that information transmission, and resulted price adjustments, across markets are closely related to the cross-sectional distribution of market depth. This finding is consistent with Duarte and Young (2008) in which part of PIN defined by Easley and O'Hara (2004) is priced by illiquidity. Overflow of orders caused by illiquidity in the sense of Amihud (2002) affects PIN regardless of information asymmetry. As our evidence suggests that price adjustment starts from markets with less depth, where information asymmetry is higher, we could interpret the transmission process of adjustment as liquidity-induced. So information asymmetry as the first part of PIN drives price adjustment within a market with less depth, and then passes the adjustment over to the deeper markets, through the second component of PIN. Our results on price adjustments across markets would help understanding recent events in international markets where volatility affects one another. According to Duarte and Young (2008), PIN would be priced more in the market with less depth and induce price adjustment subsequently. It would be more effective to alleviate potential impacts of volatility spread-over starting from the market with the least depth.

V. Conclusions

This study shows that performance of forecasts can be greatly enhanced when incorporating liquidity in the estimation of yield curve. Concentration and uneven distribution of liquidity is common in the fixed income securities market, especially in a less developed one. The degree of liquidity concentration and the premium arising from informational asymmetry has been widely examined in the literature. Studies such as Subramanian (2001) and Dutta, Basu and Vaidyanathan (2005) propose a liquidity-weighting scheme in fitting term structure. The rationale for such a weighting scheme, however, has not been formally investigated. This study presents not only basic evidence for its justification, but also related influences on market phenomenon. First of all, fitting term structure while conditioning on liquidity enhances forecasting performance and reduces informational asymmetry. Moreover, an information flow from bond markets with less depth to more contributes to the efficient absorption of informational asymmetry in prices through the trading process. This finding is consistent with transmission of price adjustments recently across volatile international financial markets with different levels of liquidity. Informational asymmetry induces volatile trading first and then price adjustment is transmitted to another market due to overflow of orders. Our analysis in this study can help understanding how market movements affect one another.

The importance of our liquidity-adjusted analysis is not so much in the fitted term structure itself, but in the implications brought forward by the behavior of extended forecasting performances. We find that the incorporation of liquidity improves forecasting performance significantly and provides a justification for its implementation, and its results are consistent with predictions of underlying theoretical models. Forecasted errors produced by liquidity-weighted fitting process are smaller in absolute term, and also in variance, than those generated by an unweighted method. Analysis on the degree of informational asymmetry also leads us to find that liquidity-based estimation helps reducing it. The longer the forecasting window is the more pronounced these effects become. More liquid issues enjoy more rapid reduction of informational asymmetry, a notion consistent with the clientele equilibrium of Vayanos and Wang (2006) where more liquid market reaches equilibrium earlier than the less liquid ones.

Further examination of forecasted price errors provides us with more insights on the reduction of informational asymmetry. Price shocks from the shorter term or less liquid issues tend to lead the corresponding shocks from trading in the longer term or more liquid issues. Informational asymmetry tends to be smaller when that mechanism is in place, but not vice versa. These phenomena are only true when liquidity is taken into account in forming price forecasts. The evidence of dynamic informationinduced price adjustment across markets disappears once price forecasts are no longer conditioned on liquidity. So liquidity is again important as it helps information to flow among markets.

Our results contribute to the pricing practice of fixed income securities. We provide a justification for the empirical literatures that applying liquidity adjustment in the estimation of term structure of emerging markets. Liquidity adjustment is necessary not just for technical reasons, but also for capturing price premium arising from static market structure and dynamic information dissemination, which is crucial to fixed income portfolio management.

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TABLE 1
Distribution of Average Weights across Issues

Two schemes of weight construction are used to produce weights, which are averaged first over all the days where transaction prices are available, and then over the first 30 trading days. The first scheme follows (5) and is proportional to the squared root of trading volume. The second scheme adds the duration of the respective issue to the raw weight defined in (5).

Issues	**Trading Period**[*]	**Liquidity Weighted**		**Liquidity and Duration Weighted**	
		Entire Period	*First 30 Trading Days*	*Entire Period*	*First 30 Trading Days*
2-year					
A92101	03.01.10~05.01.09	0.0132	0.0241	0.0168	0.0227
A92105	03.05.16~05.05.15	0.0114	0.0375	0.0156	0.0278
A93101	04.01.09~05.01.08	0.0251	0.0460	0.0217	0.0351
A93105	04.04.15~06.04.14	0.0327	0.0795	0.0193	0.0244
A94101	05.01.07~06.12.30	0.0453	0.0881	0.0161	0.0199
5-year					
A92102	03.01.17~06.12.30	0.0092	0.0115	0.0226	0.0335
A92106	03.07.15~06.12.30	0.0124	0.0227	0.0211	0.0309
A92108	03.10.30~06.12.30	0.0396	0.1044	0.0303	0.0402
A93102	04.01.30~06.12.30	0.0425	0.1791	0.0293	0.0458
A93107	04.07.22~06.12.30	0.0628	0.1358	0.0315	0.0443
A94102	05.07.22~06.12.30	0.0881	0.1442	0.0308	0.0370
10-year					
A92104	03.03.07~06.12.30	0.1887	0.5508	0.0633	0.1002
A92107	03.09.19~06.12.30	0.1722	0.6776	0.0640	0.1466
A92110	03,12.05~06.12.30	0.1439	0.6885	0.0615	0.1397
A93108	04.09.15~06.12.30	0.1968	0.6162	0.1117	0.1555
A94104	05.06.04~06.12.30	0.1947	0.6551	0.0741	0.1301
A94107	05.09.12~06.12.30	0.2193	0.6007	0.0723	0.1337
20-year					
A92103	03.02.18~06.12.30	0.0646	0.1091	0.0801	0.1383
A93103	04.02.10~06.12.30	0.0759	0.1457	0.0827	0.1526
A93109	04.11.18~06.12.30	0.0692	0.1291	0.0894	0.1629
A94103	05.02.25~06.12.30	0.0723	0.1334	0.0869	0.1478

[*] Trading period characterizes when the issue has active trading, where there are transaction prices for consecutive days. All the statistics are computed, however, only for the first three trading months.

TABLE 2
Summary Statistics of One-day-ahead Forecasted Price Errors
first three trading months

Fitted price errors are computed by subtracting forecasted prices from the actual transaction prices. The forecasted prices are derived by applying parameters estimated with the NSS method to the cash flow data on the forecasting day. Forecasted prices are only constructed for the first three trading months to assure validity and continuity.

Issues	**Unweighted**				**Liquidity Weighted**			
	Min	*Median*	*Std. Dev.*	*Max.*	*Min.*	*Median*	*Std. Dev.*	*Max.*
2-year								
A92101	-1.5145	0.0353	0.7766	1.8232	-0.7617	0.4169	1.0324	3.4701
A92105	-1.6901	0.0454	0.7645	1.8993	-0.8187	0.2155	0.9509	3.6229
A93101	-3.6236	0.0968	0.9037	1.9404	-0.7720	0.5754	1.1794	3.8640
A93105	-1.5228	0.1003	0.7267	1.7644	-0.5225	0.5795	0.9050	3.2737
A94101	-1.4768	0.1202	0.6355	1.5413	-0.5034	0.4469	0.9746	3.1116
5-year								
A92102	-3.8543	-0.1103	1.1104	2.6379	-3.4241	-0.1715	1.1703	2.9245
A92106	-3.8881	-0.0442	1.0603	2.2034	-3.6231	-0.1447	1.0838	2.8100
A92108	-3.6657	0.2539	1.2196	2.9711	-3.1304	-0.1556	1.1522	2.9385
A93102	-3.6999	0.6166	0.9232	1.7880	-2.7997	0.0399	0.9901	2.6231
A93107	-2.7101	0.7422	0.8989	1.9234	-2.9218	0.0200	1.0111	2.7667
A94102	-2.6245	0.0110	0.8553	1.5108	-2.4434	0.1118	0.9220	2.5003
10-year								
A92104	-4.1769	-1.1198	1.3075	3.4702	-6.7762	-3.8918	2.7101	2.5334
A92107	-4.8448	-1.0032	1.2223	3.8551	-5.9008	-3.1179	1.7003	2.2097
A92110	-4.0039	-0.0330	0.9101	3.7700	-7.1136	-4.6432	1.6694	1.9303
A93108	-4.7221	-0.7286	1.0143	4.0191	-6.6622	-3.6936	1.5421	2.1140
A94104	-4.4099	-1.0211	1.2306	3.1732	-5.2457	-3.2001	1.3006	2.0206
A94107	-3.3330	-0.4005	0.8921	2.9793	-5.4338	-2.4567	1.1255	1.7577
20-year								
A92103	-2.7323	0.3331	1.1996	3.0230	-1.8987	0.4672	0.9037	3.8524
A93103	-2.1586	0.0880	1.3407	4.4997	-2.2429	0.1105	0.8245	4.2370
A93109	-1.6224	0.4907	1.2138	3.6693	-2.0243	0.1993	0.8909	3.9112
A94103	-1.8867	0.2181	1.3235	4.3101	-1.6556	0.3835	0.7446	3.7678

[*] Trading period characterizes when the issue has active trading, where there are traded prices for consecutive days. All the statistics are computed, however, only for the first three trading months.

TABLE 3

Time Series Models for Various Issues

Unweighted and Liquidity-Weighted

Estimated NSS parameters from the unweighted and liquidity-weighted models are filtered through an ARIMA model to obtain forecasted prices. The model is selected for its overall performance across all issues and models according to the Schwartz Bayesian Criterion and Durbin-Watson statistics. The adjusted R-square's of the filter are compared across forecasted errors from the two fitting models. Issues with limited number of consecutive trading days are excluded for the reliability of comparisons.

Issue Code	*Unweighted*	*Liquidity Weighted*
2-year		
Beta0	ARMA(2,2)	ARMA(5,1)
Beta1	ARMA(2,1)	ARMA(5,1)
Beta2	ARMA(2,1)	ARMA(5,1)
Beta3	ARMA(2,1)	ARMA(5,1)
5-year		
Beta0	ARMA(2,1)	ARMA(4,1)
Beta1	ARMA(2,1)	ARMA(4,1)
Beta2	ARMA(2,1)	ARMA(4,1)
Beta3	ARMA(2,1)	ARMA(4,1)
10-year		
Beta0	ARMA(1,1)	ARMA(3,1)
Beta1	ARMA(1,1)	ARMA(3,1)
Beta2	ARMA(1,1)	ARMA(3,1)
Beta3	ARMA(1,1)	ARMA(3,1)
20-year		
Beta0	ARMA(2,2)	ARMA(5,1)
Beta1	ARMA(2,1)	ARMA(5,1)
Beta2	ARMA(2,1)	ARMA(5,1)
Beta3	ARMA(2,1)	ARMA(5,1)

TABLE 4

Forecasted Errors and Asymmetric Information Measure (AIM) of Given Horizons, 2-year issue (A95104)

The Asymmetric Information Measure, AIM^{a}, is computed according to (2). The left panel reports results for the entire period when traded data is available while the right panel does it only for the first 90 calendar days since its issuing day. Issues with limited number of consecutive trading days are excluded for the reliability of comparisons.

	Entire sample			On-the-run		
	Unweighted	*Liquidity Weighted*	AIM^{a}	*Unweighted*	*Liquidity Weighted*	AIM^{a}
5-day			0.9623			0.9467
MAE	1.1154	0.3385		0.8234	0.2153	
Variance	0.9867	0.0372		0.6153	0.0348	
No. of Obs.	95	95		52	52	
t-statistic[a]	7.8617 ***			8.1542 ***		
10-day			0.9757			0.9599
MAE	1.1306	0.3430		0.8391	0.2248	
Variance	1.1092	0.0269		0.6411	0.0257	
No. of Obs.	90	90		52	52	
t-statistic	7.2787 ***			7.8304 ***		
20-day			0.9623			0.9359
MAE	1.3104	0.3764		0.9942	0.2474	
Variance	1.1840	0.0446		0.6526	0.0418	
No. of Obs.	80	80		52	52	
t-statistic	8.1488 ***			8.5790 ***		
30-day			0.9451			0.9218
MAE	1.5221	0.4202		1.1163	0.2857	
Variance	1.1751	0.0645		0.6728	0.0526	
No. of Obs.	70	70		52	52	
t-statistic	8.5792 ***			9.2680 ***		

[a] The t-statistic is constructed as $t = \frac{d_t}{S_d / \sqrt{N}}$, where d_t follows (10) and $S_d = \sqrt{\frac{\sum_{t=1}^{n}(d_t - \bar{d})}{N-1}}$ and $\bar{d} = \frac{\sum_{t=1}^{N} d_t}{N}$.

*** Significant at 99%.

TABLE 5

Forecasted Errors and Asymmetric Information Measure (AIM) of Given Horizons, 5-year issues

The Asymmetric Information Measure, AIM^a, is computed according to (2). The left panel for each issue reports results for the entire period when traded data is available while the right panel does it only for the first 90 calendar days since issuing day. Issues with limited number of consecutive trading days are excluded for the reliability of comparisons.

	A95101						**A95105**					
	Entire sample			On-the-run			Entire sample			On-the-run		
	Unweighted	*Liq. Weighted*	***AIM***^{a}	*Unweighted*	*Liq. Weighted*	***AIM***^{a}	*Unweighted*	*Liq. Weighted*	***AIM***^{a}	*Unweighted*	*Liq. Weighted*	***AIM***^{a}
5-day			0.8629			0.8416			0.9348			0.8596
MAE	1.4107	0.4373		1.1995	0.3420		1.4282	0.3416		1.1221	0.3135	
Variance	0.9508	0.1303		0.6278	0.0994		0.8628	0.0562		0.6031	0.0847	
No. of Obs.	217	217		63	63		108	108		53	53	
t-statistic	14.7524 ***			16.3211 ***			11.3870 ***			10.2098 ***		
10-day			0.8916			0.8179			0.8184			0.7933
MAE	1.4710	0.4269		1.2845	0.3571		1.4854	0.5638		1.2674	0.4131	
Variance	1.0992	0.1191		0.7552	0.1375		0.9640	0.1751		0.7253	0.1499	
No. of Obs.	217	217		63	63		103	103		53	53	
t-statistic	14.8578 ***			16.6879 ***			8.8783 ***			9.7941 ***		
20-day			0.8817			0.8090			0.7307			0.7183
MAE	1.6212	0.4160		1.5734	0.4022		1.5438	0.5652		1.4239	0.4653	
Variance	1.1215	0.1326		0.7995	0.1527		0.7516	0.2024		0.7314	0.2060	
No. of Obs.	202	202		63	63		93	93		53	53	
t-statistic	16.7037 ***			16.8542 ***			9.3623 ***			11.9671 ***		
30-day			0.8247			0.7887			0.7377			0.6945
MAE	1.7614	0.4367		1.8873	0.4344		1.6059	0.5895		1.5293	0.5165	
Variance	1.1818	0.2071		0.8108	0.1713		0.8695	0.2281		0.7816	0.2388	
No. of Obs.	192	192		63	63		83	83		53	53	
t-statistic	16.7375 ***			17.0123 ***			8.4775 ***			7.9354 ***		

*** Significant at 99%.

TABLE 6

Forecasted Errors and Asymmetric Information Measure (AIM) of Given Horizons, 10-year issues

The Asymmetric Information Measure, AIM^a, is computed according to (2). The left panel for each issue reports results for the entire period when traded data is available while the right panel does it only for the first 90 calendar days since issuing day. Issues with limited number of consecutive trading days are excluded for the reliability of comparisons.

	A95103						**A95106**					
	Entire sample			On-the-run			Entire sample			On-the-run		
	Unweighted	*Liq. Weighted*	AIM^a	*Unweighted*	*Liq. Weighted*	AIM^a	*Unweighted*	*Liq. Weighted*	AIM^a	*Unweighted*	*Liq. Weighted*	AIM^a
5-day			0.7896			0.7701			0.8311			0.7392
MAE	1.7750	0.7164		1.1713	0.3631		1.3663	0.4369		1.2714	0.4049	
Variance	2.3665	0.4977		0.5255	0.1208		0.8536	0.1441		0.5531	0.1342	
No. of Obs.	186	186		62	62		74	74		48	48	
t-statistic	8.9802 ***			10.8725 ***			7.6066 ***			7.6932 ***		
10-day			0.9486			0.7574			0.8653			0.7620
MAE	1.8902	0.4394		1.7421	0.3821		1.3911	0.4571		1.3692	0.4431	
Variance	2.5821	0.1327		0.5347	0.1297		0.9756	0.1314		0.6178	0.1470	
No. of Obs.	181	181		62	62		69	69		48	48	
t-statistic	12.4412 ***			10.2004 ***			6.8780 ***			6.9356 ***		
20-day			0.9447			0.7441			0.7702			0.7602
MAE	2.0398	0.4388		1.8663	0.4062		1.1437	0.5074		1.1194	0.4753	
Variance	2.6768	0.1479		0.5652	0.1446		0.6451	0.1482		0.6289	0.1508	
No. of Obs.	171	171		62	62		59	59		48	48	
t-statistic	16.7037 ***			10.7910 ***			9.3623 ***			9.9645 ***		
30-day			0.9207			0.6870			0.6968			0.6949
MAE	2.1594	0.4617		1.9805	0.4240		1.0361	0.4491		1.0873	0.4334	
Variance	2.9286	0.2321		0.6237	0.1952		0.3447	0.1045		0.3464	0.1057	
No. of Obs.	161	161		62	62		49	49		48	48	
t-statistic	12.8457 ***			13.8727 ***			5.8168 ***			6.9354 ***		

*** Significant at 99%.

TABLE 7

Vector AutoRegressive (VAR) Regressions and Corresponding AIM's in Forecasting Period
Unweighted and Liquidity-weighted

One-day-ahead forecast price errors, both unweighted and liquidity-weighted, are used in Vector Autoregressive regressions on data in the forecast period of 2006. Error series for issues in the four panels respectively with the errors of the header issue of each panel as the dependent variable. Each regression takes the VAR form as follows,

$$FE_t^j = \beta_0 + \sum_{i=1}^{n}\sum_{k=1}^{l}\beta_{ik} FE_{t-k} + \varepsilon_t,\ j = 1, 2 \ldots n$$

where *FE* stands for one-day-ahead forecasted error of respective issue, *n* is the number of concurrently traded issues within the given period, *j* is a specific issue among these issues and *l* is the number of lags for the given VAR model. Order of lags in each panel is determined by the Akaike information criteria and is shown in parentheses by panel headers. Observations are dropped if there are missing prices for any given issue in the group. The columns report the VAR coefficients (when applicable) and their standard deviations, in parenthesis, for groups of *FE*'s matched according to trading dates in Table 1. The R^2 of each respective regression is defined as AIM^b, which is monotonic in the original *AIM* as defined by Burlacu, *et al*. (2007).

	Unweighted		**Liquidity-weighted**	
	β_{i1}	β_{i2}	β_{i1}	β_{i2}
Panel (a): March 31, 2006 to May 11, 2006 (1 lag, 21 obs.)				
5-year (A95101), on-the-run				
5-year (A95101)	0.2676 (0.1132)**		0.3259 (0.0894)**	
10-year (A95103)	0.0797 (0.1091)		0.0681 (0.0822)	
20-year (A95102)	0.0724 (0.1253)		-0.0239 (0.0805)	
***AIM^b*:**	**0.1719**		**0.2238**	
10-year (A95103), on-the-run				
5-year (A95101)	0.1942 (0.1128)		0.1942 (0.0961)*	
10-year (A95103)	0.3383 (0.1711)*		0.4922 (0.1430)**	
20-year (A95102)	-0.0366 (0.1284)		0.1159 (0.0833)	
***AIM^b*:**	**0.1335**		**0.2951**	
20-year (A95102), on-the-run				
5-year (A95101)	0.1928 (0.1103)		0.2142 (0.1018)*	
10-year (A95103)	0.1974 (0.1780)		0.1534 (0.1430)	
20-year (A95102)	0.2640 (0.1292)*		0.3759 (0.0896)**	
***AIM^b*:**	**0.1558**		**0.3103**	
Panel (b): May 12, 2006 to July 19, 2006 (1 lag, 37 obs.)				
2-year (A95104), on-the-run				
2-year (A95104)	0.1568 (0.0773)*		0.1384 (0.0676)*	
5-year (A95101)	0.1045 (0.0755)		0.1270 (0.0661)	
10-year (A95103)	-0.0067 (0.0649)		0.1002 (0.0568)	
20-year (A95102)	-0.0142 (0.0693)		0.0905 (0.0539)	
***AIM^b*:**	**0.2151**		**0.3119**	

5-year (A95101), on-the-run

2-year (A95104)	0.0921 (0.1096)	0.0960 (0.0826)
5-year (A95101)	0.2776 (0.0944)**	0.3532 (0.0803)**
10-year (A95103)	0.0660 (0.0858)	0.0702 (0.0817)
20-year (A95102)	0.1006 (0.1244)	0.1198 (0.0885)
AIM^b **:**	**0.2386**	**0.2990**

10-year (A95103), on-the-run

2-year (A95104)	-0.0178 (0.0965)	-0.0185 (0.0948)
5-year (A95101)	0.1239 (0.0868)	0.2843 (0.0526)**
10-year (A95103)	0.2735 (0.1118)**	0.3991 (0.1019)**
20-year (A95102)	0.1540 (0.1082)	0.1769 (0.0936)
AIM^b **:**	**0.3614**	**0.3992**

20-year (A95102), on-the-run

2-year (A95104)	-0.0380 (0.1155)	-0.0469 (0.0936)
5-year (A95101)	0.1919 (0.1289)	0.2557 (0.0929)**
10-year (A95103)	0.1406 (0.0993)	0.1164 (0.1026)
20-year (A95102)	0.2263 (0.0949)**	0.2430 (0.0889)**
AIM^b **:**	**0.2889**	**0.3687**

Panel (c): July 20, 2006 to September 7, 2006 (2 lags, 27 obs.)

2-year (A95104), on-the-run

2-year (A95104)	0.2342 (0.0639)**	0.2615 (0.0551)**	0.1218 (0.0579)*
5-year (A95105)	-0.0098 (0.0623)	-0.0042 (0.0597)	0.0830 (0.0611)
5-year (A95101)	-0.0138 (0.0868)	0.1291 (0.0588)*	0.0903 (0.0634)
10-year (A95103)	0.0954 (0.0743)	0.0857 (0.0590)	0.0211 (0.0401)
20-year (A95102)	0.0643 (0.0674)	0.1124 (0.0595)	0.1041 (0.0574)
AIM^b **:**	**0.2404**	**0.4723**	

5-year (A95105), on-the-run

2-year (A95104)	0.1604 (0.0995)	0.2360 (0.0875)**	0.2006 (0.1003)*
5-year (A95105)	0.1556 (0.0773)*	0.3621 (0.0768)**	0.1454 (0.0922)
5-year (A95101)	0.2733 (0.0719)**	0.3776 (0.0756)**	0.1992 (0.0894)*
10-year (A95103)	0.1064 (0.0943)	0.0991 (0.0749)	0.0912 (0.0825)
20-year (A95102)	-0.0197 (0.0835)	0.1118 (0.0711)	0.1439 (0.0799)
AIM^b **:**	**0.3565**	**0.5036**	

5-year (A95101), off-the-run

2-year (A95104)	0.1005 (0.0714)	0.1256 (0.0637)*	0.1019 (0.0698)
5-year (A95105)	0.1126 (0.0688)	0.0842 (0.0671)	0.0895 (0.0721)
5-year (A95101)	0.2180 (0.0595)*	0.3126 (0.0556)**	0.1237 (0.0705)
10-year (A95103)	0.1011 (0.0793)	0.1171 (0.0638)	0.1033 (0.0665)
20-year (A95102)	-0.0122 (0.0892)	0.1028 (0.0679)	0.0773 (0.0792)
AIM^b **:**	**0.3006**	**0.4244**	

10-year (A95103), on-the-run

2-year (A95104)	0.2033 (0.1384)	0.2171 (0.0726)**	0.1996 (0.0729)**
5-year (A95105)	0.1326 (0.1003)	0.1487 (0.0773)	0.1335 (0.0796)
5-year (A95101)	0.1177 (0.0928)	0.4776 (0.0705)**	0.2192 (0.0756)**
10-year (A95103)	0.2889 (0.0606)**	0.4009 (0.0641)**	0.1255 (0.0783)
20-year (A95102)	0.1353 (0.0884)	0.1424 (0.0679)*	0.1039 (0.0648)
AIM**:**	**0.4743**	**0.5896**	

20-year (A95102), on-the-run			0.5579
2-year (A95104)	-0.0044 (0.0823)	0.1674 (0.0751)*	0.1261 (0.1111)
5-year (A95105)	0.1335 (0.0934)	0.1203 (0.0828)	0.1005 (0.0907)
5-year (A95101)	0.1139 (0.0857)	0.2649 (0.0712)**	0.1536 (0.0720)*
10-year (A95103)	0.1054 (0.0912)	0.1116 (0.0764)	0.0998 (0.0777)
20-year (A95102)	0.3969 (0.0747)**	0.2975 (0.0734)**	0.1661 (0.0797)*
AIM ^{b} **:**	**0.3499**	**0.5579**	

Panel (d): September 8, 2006 to November 9, 2006 (2 lags, 31 obs.)

2-year (A95104), on-the-run			
2-year (A95104)	0.2519 (0.0638)**	0.1587 (0.0784)*	0.1246 (0.0725)
5-year (A95105)	0.1247 (0.0834)	0.0994 (0.0606)	0.0814 (0.0645)
5-year (A95101)	0.1006 (0.0624)	0.1133 (0.0643)	0.0823 (0.0748)
10-year (A95106)	0.0989 (0.0881)	0.0677 (0.0808)	0.0359 (0.0769)
10-year (A95103)	0.1272 (0.0967)	0.0838 (0.0840)	0.0666 (0.0792)
20-year (A95102)	-0.0263 (0.0854)	-0.0009 (0.0886)	0.0996 (0.0698)
AIM ^{b} **:**	**0.3138**	**0.4913**	
5-year (A95105), on-the-run			
2-year (A95104)	0.2663 (0.0850)**	0.1910 (0.0779)**	0.1637 (0.0823)*
5-year (A95105)	0.2430 (0.0749)**	0.1854 (0.0657)**	0.1801 (0.0992)
5-year (A95101)	0.3869 (0.0635)**	0.1948 (0.0610)**	0.1654 (0.0764)*
10-year (A95106)	0.0611 (0.0878)	0.1005 (0.0993)	0.0858 (0.0808)
10-year (A95103)	0.1108 (0.0886)	0.0991 (0.0749)	0.0912 (0.0825)
20-year (A95102)	0.1056 (0.0798)	0.1218 (0.0711)	0.1221 (0.0894)
AIM ^{b} **:**	**0.3248**	**0.5361**	
5-year (A95101), off-the-run			
2-year (A95104)	0.0761 (0.0968)	0.1625 (0.0968)	0.1311 (0.0967)
5-year (A95105)	0.1204 (0.1015)	0.1531 (0.0994)	0.1219 (0.0976)
5-year (A95101)	0.2004 (0.0907)*	0.1895 (0.0931)*	0.1247 (0.0899)
10-year (A95106)	0.1669 (0.1121)	0.1141 (0.0967)	0.0858 (0.0808)
10-year (A95103)	0.0532 (0.1295)	0.0429 (0.0856)	0.0212 (0.0767)
20-year (A95102)	0.1394 (0.1136)	-0.0123 (0.0895)	0.1037 (0.0949)
AIM ^{b} **:**	**0.3352**	**0.4370**	
10-year (A95106), on-the-run			
2-year (A95104)	0.1119 (0.0845)	0.4425 (0.0622)**	0.2008 (0.0637)**
5-year (A95105)	0.1348 (0.0892)	0.3137 (0.0643)**	0.1770 (0.0690)**
5-year (A95101)	0.1219 (0.0937)	0.4786 (0.0567)**	0.1964 (0.0698)**
10-year (A95106)	0.4087 (0.0775)**	0.1117 (0.0626)	0.1006 (0.0728)
10-year (A95103)	0.4382 (0.0814)**	0.1666 (0.0833)*	0.1337 (0.0759)
20-year (A95102)	0.1333 (0.0831)	0.1446 (0.0815)	0.1221 (0.0868)
AIM ^{b} **:**	**0.5777**	**0.6399**	
10-year (A95103), off-the-run			
2-year (A95104)	0.1335 (0.0823)	0.1707 (0.0758)*	0.1365 (0.0724)
5-year (A95105)	0.1390 (0.0765)	0.1757 (0.0796)*	0.1229 (0.0815)
5-year (A95101)	0.1146 (0.0692)	0.1542 (0.0607)**	0.1031 (0.0995)
10-year (A95106)	0.2397 (0.0611)**	0.1117 (0.0626)	0.1006 (0.0728)
10-year (A95103)	0.2919 (0.0894)**	0.1779 (0.0848)*	0.1337 (0.0759)
20-year (A95102)	0.1184 (0.0721)	0.1038 (0.0659)	0.0886 (0.0842)
AIM ^{b} **:**	**0.4995**	**0.4665**	

20-year (A95102), on-the-run

2-year (A95104)	-0.0035 (0.0718)	0.1514 (0.0738)*	0.1403 (0.0811)
5-year (A95105)	0.1103 (0.0700)	0.1601 (0.0613)**	0.0832 (0.1094)
5-year (A95101)	-0.0195 (0.0695)	0.1761 (0.0641)**	0.1699 (0.0823)*
10-year (A95106)	0.0598 (0.1027)	0.0420 (0.0922)	0.0318 (0.0919)
10-year (A95103)	0.0347 (0.0704)	0.0746 (0.0712)	0.0237 (0.0877)
20-year (A95102)	0.2558 (0.0723)**	0.2992 (0.0776)**	0.1555 (0.0829)
AIM[b] **:**	**0.3818**	**0.5611**	

* Significant at 95%.

** Significant at 99%.