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Are Liquidity and Information Risks Priced in the Treasury Bond Market?

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ABSTRACT

We provide a comprehensive empirical analysis of the effects of liquidity and information risks on expected returns of Treasury bonds. We focus on the systematic liquidity risk of Pastor and Stambaugh as opposed to the traditional microstructure-based measures of liquidity. Information risk is measured by the probability of information-based trading (PIN). We document a strong positive relation between expected Treasury returns and liquidity and information risks, controlling for the effects of other systematic risk factors and bond characteristics. This relation is robust to many empirical specifications and a wide variety of traditional liquidity and informed trading proxies.

THE IMPORTANCE OF LIQUIDITY and information risks for asset pricing has been increasingly recognized in the literature. For example, in her 2003 American Finance Association presidential address, O'Hara (2003, p. 1335) argues that, "Markets have two important functions—liquidity and price discovery—and these functions are important for asset pricing." She also suggests that standard asset pricing models fail to adequately capture asset price behavior because they assume that the underlying problems of liquidity and price discovery have been resolved.

Recent attempts to incorporate liquidity and information risk factors into asset pricing models have generated important insights into asset price behavior. In an influential study, Pastor and Stambaugh (2003) show that marketwide liquidity is a state variable that is important for pricing common stocks. In particular, they find that expected stock returns are positively related to the

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sensitivity of returns to innovations in aggregate liquidity.[1] In a separate study, Easley, Hvidkjaer, and O'Hara (2002, hereafter EHOH) argue that a firm's information structure affects its equilibrium return because investors demand compensation for holding stocks with risk of information-based trading. They document a significant positive relation between expected stock returns and PIN (probability of information-based trading), a measure of information risk derived from a sequential trade model.[2]

While these studies focus on the effects of either liquidity or information risk on expected stock returns, we provide the first comprehensive empirical analysis of the effects of liquidity and information risks on expected returns of U.S. Treasury bonds. The U.S. Treasury market is one of the largest and most important financial markets in the world. The daily trading volume in the U.S. Treasury market reached \$600 billion in 2006 compared to only about \$110 billion in the U.S. stock market. From an investment perspective, it is important to understand the determinants of required Treasury returns. Moreover, returns of default-free bonds contain information that is essential for pricing all other financial assets. Understanding Treasury bond returns is therefore an integral part of any unified theory of asset pricing.

Using a large transaction data set of U.S. Treasury securities provided by GovPX, we estimate the marketwide liquidity factor and PIN based on the approaches of Pastor and Stambaugh (2003) and EHOH (2002), respectively. We then examine the cross-sectional relation between expected Treasury bond return and both liquidity beta (the sensitivity of bond returns to innovations in the systematic liquidity risk factor) and PIN by controlling for the effects of other systematic risk factors, bond characteristics, and a wide variety of liquidity and informed trading proxies used in the existing literature. By jointly considering the standard and nonstandard risk factors in a unified empirical asset pricing model, our paper makes several unique contributions to the literature.

First, our study represents the first extension of Pastor and Stambaugh's (2003) study to the Treasury bond market. Liquidity has been recognized as an important factor for bond pricing. Pastor and Stambaugh (2003) use Long-Term Capital Management, a hedge fund that invested in fixed income securities

[1] Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan et al. (1998), and Amihud (2002), among others, have shown that traditional microstructure-based measures of liquidity, such as bid-ask spread, significantly affect expected stock returns. Chordia, Roll, and Subrahmanyam (2000, 2001) find commonality in liquidity across stocks, while Chordia, Subrahmanyam, and Anshuman (2001) find that stocks with more variable liquidity have lower expected returns. Pastor and Stambaugh (2003) differ from these studies by focusing on marketwide liquidity as a state variable that affects the well being of investors. Acharya and Pedersen (2005) also study asset pricing with liquidity risk.

[2] Other studies that explore the role of asymmetric information in asset pricing include, among others, Grossman and Stiglitz (1980), Wang (1993), and Easley and O'Hara (2004). Grossman and Stiglitz (1980) show that when differential information is not fully revealed in equilibrium, individual investors face differing risk-return trade-offs. Wang (1993) shows that uninformed traders demand a premium for the risk of trading with informed traders in the presence of asymmetric information. Easley and O'Hara (2004) develop a rational expectations model to show that in equilibrium uninformed traders require compensation to hold stocks with asymmetric information.

extensively, as an example to motivate their concept of systematic liquidity risk. The well-known "flight-to-quality" phenomenon suggests that when the stock market faces heavy selling pressure, the government bond market typically encounters heavy buying pressure, although trading volume is high in both markets. This suggests that the direction of order imbalance and the nature of liquidity risk could be quite different for the Treasury bond market (see Beber, Brandt, and Kavajecz (2007)). Pastor and Stambaugh (2003) suggest that, "It would also be useful to explore whether some form of systematic liquidity risk is priced in other financial markets, such as fixed income markets or international equity markets." In this paper, we explore whether the liquidity risk in the Pastor–Stambaugh sense plays a significant role in the pricing of Treasury securities.

Second, besides liquidity risk, we consider the effect of information risk on expected Treasury returns. Recent studies have shown that asymmetric information exists in the Treasury bond market, even though government bond prices are mainly affected by public information. While private information in the stock market is predominantly inside information about a firm's cash flows, private information in the government bond market mainly derives from heterogeneous interpretation of public information (Green (2004), Brandt and Kavajecz (2004)) or private observations of investors' order flows by dealers (Lyons (2001)). Though investors observe the same set of public information, they differ in their abilities to analyze the information. For example, a large investment bank may have more skilled analysts or use more sophisticated models to analyze public information than a pension fund. This heterogeneity can create information disparity among traders similar to the effect of private information in the traditional sense. In addition, by observing investors' order flow, dealers know the intentions of their clients, which provides valuable information for predicting future short-term price movements even if trading provides no fundamental information about security value.[3] The over-the-counter (OTC) trading mechanism of the bond market also may make investors more vulnerable to adverse information.[4] To capture this asymmetric information effect on Treasury pricing, we employ the PIN measure of EHOH, which has proven to be quite effective for identifying information risk of security trading. By considering both the Pastor–Stambaugh liquidity measure and PIN, we estimate the effects of both liquidity and information risks on expected Treasury returns.

[3] It also has been documented that order flow contains private information in the foreign exchange market due to similar reasons (see Lyons (2001) for a review of the literature on the microstructure approach to exchange rates).

[4] In the OTC bond market, dealers post their own bid-ask quotes and each observes only a portion of order flows. Since order flow is an important piece of information to identify informed trades, OTC dealers may not be able to infer the presence of informed traders as effectively as specialists in the NYSE who can observe the entire order flow. Furthermore, the bond market is less transparent. Retail investors in the bond market do not enjoy the same access to information as investors in the stock market.

Third, we provide evidence that liquidity and information risks are priced in the Treasury market. We show that the marketwide liquidity factor of Pastor and Stambaugh (2003) and PIN of EHOH (2002) estimated using trade data of individual bonds capture very well the liquidity condition and information-based trading in the Treasury bond market, respectively. More important, we document a positive relation between expected bond returns and both liquidity beta and PIN. The strength of this relation is economically significant and robust to many different empirical specifications. Furthermore, this relation remains strong even after controlling for other systematic risk factors and a host of liquidity and informed trading proxies including bid-ask spread, maturity, standard deviations of bond returns and bid-ask spreads, abnormal trading volume, order imbalance, market depth, and whether a bond is on or off the run. Our results demonstrate the generality of the findings of Pastor and Stambaugh (2003) and EHOH (2002) for the Treasury market.

Finally, our results have important implications for existing theories on the term structure of interest rates. The classical liquidity premium theory of the term structure suggests that long-term bonds have higher expected returns than short-term bonds because they expose investors to greater interest rate risk. Our results show that in addition to interest rate risk, liquidity and information risk factors affect the returns of Treasury securities with different maturities.

Although both the liquidity beta of Pastor-Stambaugh (2003) and PIN of EHOH (2002) are priced in the Treasury bond market, there are important differences between these two risk measures. The marketwide liquidity of Pastor and Stambaugh (2003) is a state factor, and systematic liquidity risk captures the risk that the value of a bond will drop when marketwide liquidity is low. Because this liquidity risk is undiversifiable, investors demand compensation to bear this risk. Therefore, the liquidity risk measure represents a more standard systematic-risk approach to modeling expected bond returns. In contrast, PIN is derived from a microstructure model that mainly focuses on individual securities and is estimated from trade data of individual bonds. Thus, to a large extent, PIN represents security-specific information risk.

Our focus on the systematic liquidity risk measure of Pastor and Stambaugh (2003) differentiates our paper from most existing studies that investigate the effects of traditional microstructure-based measures of liquidity on bond yields.[5] The liquidity risk we investigate is not the risk that liquidity will be low when investors need to trade but is instead the risk that the bond's value will drop when marketwide liquidity worsens. More specifically, the risk is

[5] For example, Amihud and Mendelson (1991) find that less liquid Treasury notes have higher bid-ask spreads and yields. Fleming and Remolona (1999) investigate the response of prices, volume, and bid-ask spreads to macroeconomic announcements. Fleming (2003) examines the liquidity of the Treasury market using various measures such as spreads, trade and quote size, trading frequency, volume, and price impacts of net order flow. Chordia, Sarkar, and Subrahmanyam (2005) study liquidity in both stock and bond markets. Both studies find commonality of liquidity in the government bond market. Goldreich et al. (2005) examine the price differences between on- and off-the-run Treasuries and time varying liquidity over the on/off cycle. They show that current price of Treasuries reflects the expectation of the costs and benefits of future liquidity.

determined by how a bond's return fluctuates in association with a state variable and not by how the bond's liquidity fluctuates. Previous studies on the Treasury market focus almost exclusively on the effect of the level of liquidity on bond yields. That the level of liquidity can affect the Treasury yield is not surprising because investors incur transaction costs, which lowers a security's value by reducing its cash flow. Our paper adds value to the fixed income literature by focusing on a new dimension of the liquidity effect that has not yet been explored in the pricing of Treasuries.

Our analysis of informed trading based on the PIN measure of EHOH (2002) also goes beyond existing studies that examine the informational role of trading in the Treasury bond market. Brandt and Kavajecz (2004) show that order imbalances can explain a significant portion of day-to-day variations in government bond yields even on days without major macroeconomic announcements. Green (2004) studies the information content of price changes in 5-year Treasury notes surrounding news releases and finds that trading subsequent to information announcements aids in price discovery. Pasquariello and Vega (2007) examine the role of private and public information in the process of price formation in the U.S. Treasury market and find that daily bond price dynamics are related to fundamentals and agents' beliefs. While these studies document the importance of asymmetric information in the Treasury bond market, our study represents the first attempt to quantify the effect of information risk on expected Treasury returns regardless of whether there is a public information announcement or not.

Our empirical results for the liquidity and information risks provide new insights on the pricing of Treasury securities. First, our results show that liquidity beta plays a significant role in Treasury pricing. There is evidence that liquidity risk is important over and beyond the effect of the level of liquidity. Thus, the Pastor–Stambaugh liquidity risk measure is an important determinant of expected Treasury returns and is not a proxy for the microstructure-based liquidity measures. Second, information risk affects expected Treasury returns. Previous studies find that asymmetric information exists and order flows contain private information to move Treasury prices (Green (2004), Brandt and Kavajecz (2004)). However, it is not clear whether the information variable affects expected returns or just realized returns as the case for idiosyncratic risk. We clarify this issue by documenting a significant positive relation between expected Treasury returns and information risk in the cross-sectional regressions. Third, our results provide the relative economic significance of the effects of liquidity and information risks on cross-sectional returns. Results show that a difference of 10 percentage points in liquidity risk leads to a difference in Treasury excess return of nine basis points per annum, which accounts for 6% of the mean excess return. By contrast, the same amount of change in information risk leads to a difference in Treasury excess return of six basis points per annum or 4% of the mean excess return. Hence, while both liquidity and information matter, the economic effect of liquidity risk appears to be greater than that of information risk.

The remainder of this paper is organized as follows. In Section I, we explore the roles of liquidity and information risks in Treasury pricing and discuss the procedure for estimating systematic liquidity risk and PIN. Section II describes the intraday GovPX data set and presents empirical estimates of the Pastor–Stambaugh liquidity measure and PIN. Section III provides cross-sectional tests on the relation between expected Treasury returns and liquidity and information risks. Finally, Section IV concludes the paper.

I. Measures of Liquidity and Information Risks

In this section, we present the models and empirical methodologies for estimating liquidity and information risks for the Treasury market. We first discuss the procedure for constructing marketwide liquidity and estimating the systematic liquidity risk measure of Pastor and Stambaugh (2003) using bond return and volume data. We then describe the sequential trade model of EHOH (2002) and the estimation of PIN using trade data of individual bonds.

A. Measure of Systematic Liquidity Risk

Pastor and Stambaugh (2003) consider liquidity risk as the risk that an asset's value will drop when marketwide liquidity worsens. In this respect, marketwide liquidity plays a role similar to other systematic risk factors in standard asset pricing models, and systematic liquidity risk is defined as sensitivities of asset returns to fluctuations in marketwide liquidity factor.

The Pastor–Stambaugh model focuses on a dimension of liquidity associated with temporary price changes accompanying order flow. Lower liquidity tends to correspond to stronger price reversals the next day resulting from the order flow in a given direction on a particular day. Based on this argument, the liquidity measure for a bond in month t can be constructed from the least squares estimate of the $\pi_{i,t}$ parameter in the following regression:

$$r^e_{i,j+1,t} = \rho_0 + \rho_1 R_{i,j,t} + \pi_{i,t} sign\big(r^e_{i,j,t}\big) \cdot Vol_{i,j,t} + u_{i,j+1,t}, \qquad (1)$$

where $R_{i,j,t}$ is the return of bond i on day j, $r^e_{i,j,t} = R_{i,j,t} - R_{b,j,t}$ is the bond return in excess of the equally weighted Treasury market return, $R_{b,j,t}$, $sign(r^e_{i,j,t})$ is the signed indicator that is equal to 1 if the excess return $r^e_{i,j,t}$ is positive and -1 if it is negative, and $Vol_{i,j,t}$ is the par volume (in millions of dollars) for bond i. In our empirical investigation, (1) is estimated each month (t) using daily return and volume data only for those bonds that have at least 10 return observations per month.

The rationale behind the model in (1) is that the order flow should be accompanied by a return that will be partially reversed if the bond is not perfectly liquid. The use of the return in excess of the Treasury bond market as the dependent variable and to sign volume is intended to remove the market return effect so as to better isolate the individual bond effect of volume-related return reversals. The adjustment for the market return in this context is analogous to using the traditional market model to obtain the idiosyncratic return component with the implicit assumption of a unit market beta. The objective here is to first obtain a measure of liquidity at the individual security level based on the idiosyncratic returns and then aggregate across securities to get a marketwide or average liquidity variable.

The model in (1) is estimated for each individual bond. To the extent that bonds have different durations and other characteristics, returns vary with these characteristics. The liquidity measure of each individual bond estimated from (1) is then aggregated over all bonds (N) month by month:

$$\hat{\pi}_t = \frac{1}{N}\sum_{i=1}^{N}\pi_{i,t}. \tag{2}$$

Systematic liquidity risk is measured as the sensitivity of bond returns to unexpected innovations in marketwide liquidity. To obtain the liquidity innovation ($\hat{e}_t$), we estimate the following regression model for the differenced liquidity series:

$$\Delta\hat{\pi}_t = a_0 + a_1\Delta\hat{\pi}_{t-1} + a_2\hat{\pi}_{t-1} + e_t. \tag{3}$$

Since the residual term for Treasury bonds is usually quite small, we multiply the estimated $\hat{e}_t$ by 1,000 to obtain

$$L_t = 1000 \cdot \hat{e}_t, \tag{4}$$

where the scaling has no effect on empirical tests and is merely used to produce a desirable range for the liquidity index and beta.

Based on the marketwide liquidity measure in (4), we estimate liquidity risk, β_L, from a time-series regression that includes the Fama–French risk factors and term premium:

$$\begin{aligned} R_{it} - R_{ft} &= \alpha_{0i} + \beta_{iMKTt}(R_{mt} - R_{ft}) + \beta_{iMKTt-1}(R_{mt-1} - R_{ft-1}) \\ &\quad + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_L L_t + \beta_{Term}TERM_t + v_t, \end{aligned} \tag{5}$$

where $R_{mt} - R_{ft}$ is the market excess return, SMB_t is the size factor, HML_t is the book-to-market factor, and $TERM_t$ is term premium equal to the difference between the monthly long-term government bond return and the 1-month Treasury bill rate R_{ft} in month t. The variable $TERM$ has been shown to play an important role in explaining bond returns (see Fama and French (1993), Campbell and Ammer (1993)) and is viewed as a proxy for the common risk factor associated with unexpected changes in interest rates. The lagged market excess return is included to account for the potential effect of nonsynchronous trading. Liquidity risk, β_L, is used along with other systematic risk measures in the cross-sectional expected return tests. We include the Fama–French three factors in our analysis because they may contain useful information for explaining expected bond returns.[6]

[6] To test the robustness of our results, we also estimate a model without the Fama–French factors and obtain similar results for both the time-series regressions and cross-sectional tests in later sections. Specifically, we find that the term premium and the liquidity factor capture most variation in Treasury returns, although the Fama–French factors marginally improve the explanatory power. These results are available from the authors upon request.

It is important to draw a difference between liquidity and liquidity risk. Traditionally, liquidity denotes the ability to trade sufficient quantities of assets quickly at low cost and without impacting the market price too much. Liquidity can be aggregated across individual security liquidities to obtain marketwide liquidity (see Chordia, Roll, and Subrahmanyam (2000)). Since liquidity changes over time, "liquidity risk" in the traditional sense is usually perceived as the risk that liquidity may be low when investors try to trade their assets.

Unlike the traditional liquidity concept, the Pastor–Stambaugh liquidity measure focuses on the aspect of liquidity associated with temporary price fluctuations induced by order flow represented by signed volume in (1). This idea is mainly based on the empirical evidence that returns associated with high volume tend to be reversed more strongly. This evidence is consistent with the notion that investors are compensated for accommodating the liquidity demand of others (see Campbell, Grossman, and Wang (1993)). Each security's liquidity is estimated from (1) and aggregated cross-sectionally to come up with the average liquidity level in (2). The liquidity factor in (4) represents unanticipated aggregate liquidity variations. With this well-defined liquidity risk factor, one can estimate systematic liquidity risk, β_L, and examine whether it is priced in the cross-section of asset returns. The liquidity risk β_L is determined by how a bond's return fluctuates with a state variable and not by how the bond's liquidity fluctuates.

Previous studies focus on the effect of the level of liquidity on expected asset returns (see, for example, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998)). These studies find that less liquid assets have higher expected returns primarily due to higher trading costs. By contrast, we investigate whether expected Treasury returns are related to systematic liquidity risk, β_L. There are important differences between the previous approach and the Pastor–Stambaugh approach used in this study. First, previous studies focus on the liquidity of individual securities, and the liquidity measures they use are security specific and thus contain an idiosyncratic component. Unlike these studies, we focus on the Pastor–Stambaugh systematic liquidity risk measure, which contains no idiosyncratic component. Second, the microstructure-based liquidity measures could be very noisy proxies for liquidity risk. For example, bid-ask spreads commonly used in cross-sectional empirical tests may be affected by factors such as inventory concerns, adverse selection, and minimum tick size.[7] The Pastor–Stambaugh liquidity risk measure, on the other hand, represents a more standard approach of systematic risk contribution to expected return and is more precisely defined as the sensitivity of Treasury returns to marketwide liquidity.

[7] Other traditional liquidity measures have a similar problem. Volume is strongly associated with volatility, which is traditionally thought to impair liquidity. Although markets with high volume tend to be more liquid, it is often the case that volume is high when liquidity is low. For example, trading volume on the NYSE set its historical record on October 19, 1987. A potential drawback of the depth variable is that market makers typically do not reveal the full quantities they are willing to transact at a given price. Therefore, the quoted depth may underestimate the true depth.

Although it focuses on a different dimension of liquidity, the Pastor–Stambaugh liquidity risk often correlates with the traditional liquidity measures. In our empirical analysis, we find that illiquid bonds also tend to have high liquidity risk. One plausible reason for this positive relation is that the investor's demand for illiquid bonds is sensitive to the aggregate liquidity condition. Investors care about liquidity, and when market liquidity worsens they will avoid holding illiquid bonds. Consider the case in which an investor faces a margin constraint and he must liquidate some assets. If he holds illiquid bonds it will be much more difficult to sell these assets to settle the margin call. Conversely, if he holds liquid bonds, it will be relatively easy to sell them to generate cash. Thus, the investor's demand for illiquid bonds will be more sensitive to aggregate liquidity changes than that for liquid bonds, which implies higher price sensitivity for illiquid bonds. Moreover, the effect of liquidity is heightened when there is "flight-to-liquidity." In times of crisis, risk-averse investors defensively rebalance their portfolios toward more liquid bonds. The price impact of trading illiquid bonds is generally higher than trading liquid bonds, and more so when market liquidity is low and sell volume is heavy. Selling illiquid bonds in an illiquid market pushes their price down much more than in the regular market. These arguments are consistent with the findings of Beber et al. (2007) that investors chase liquidity in times of market stress and liquidity becomes more important for bond valuation. Taken together, price changes of illiquid bonds tend to be more sensitive to aggregate liquidity shocks, and higher expected returns are required by investors to hold these bonds.

B. Measure of Information Risk: PIN

We employ the EHOH model to estimate the information risk or the probability of information-based trading of U.S. government bonds. This parsimonious structural model has been shown to be very effective in capturing a market maker's learning process about private information from trades. The model has been successfully implemented in previous studies (e.g., Easley, Kiefer, and O'Hara (1997a, 1997b), Easley, O'Hara, and Paperman (1998), and Easley, O'Hara, and Saar (2001)) to address many important microstructure issues.[8] The model assumes that at the beginning of each day, there is a probability α for the arrival of new information, a signal about the value of the underlying asset traded. Good news means the value of the asset is high ($\bar{V}_i$), and

[8] Although the EHOH model was derived from the trading system with a risk-neutral specialist, studies have shown that this model can be easily extended to a multiple dealer market making system. For example, Madhavan (1995) applies a similar model to a market system of multiple competitive dealers to analyze the effects of trading information disclosure on market performance. Easley, O'Hara, and Srinivas (1998) use a similar model to study the relation between option volume, stock prices, and information-based trading. Saar (2001) shows that this model applies to any trading mechanism that takes the form of a specialist (e.g., NYSE), multiple dealers (e.g., NASDAQ), or an electronic limit order book (e.g., the Paris Bourse). On the empirical front, Heidle and Huang (2002) and He and Wu (2003) use a similar model to estimate the PIN and asymmetric information costs for NASDAQ stocks. These studies suggest that the EHOH model is general enough to characterize the bond market with multiple dealers.

bad news means the value of the asset is low ($\underline{V}_i$). Good and bad news occur with probabilities1 $-\ \delta$ and δ, respectively. On each trading day, traders arrive according to independent Poisson processes throughout the day. The market maker sets prices as traders arrive, conditional on the information at the time of trade. Orders from informed traders arrive at rate μ (on information event days), and orders from uninformed buyers and sellers arrive at rates ε_b and ε_s, respectively. Informed traders buy if they have seen good news and sell if they have seen bad news.

The structural parameters of the EHOH model can be easily estimated using trade data. EHOH show that the likelihood function of the model for a single trading day can be written as

$$L(\theta \mid B, S) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_S}\frac{\varepsilon_s^S}{S!} + \alpha(1-\delta)\,e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!}, \tag{6}$$

where B and S are the total number of buy and sell orders for that day, respectively, and $\theta = (\alpha, \mu, \varepsilon_b, \varepsilon_s, \delta)$ is the vector of model parameters. The above likelihood function has an intuitive interpretation. On a no-news day, which happens with probability $1-\alpha$, buy and sell orders are purely from uninformed traders who arrive with intensities ε_b for buyers and ε_s for sellers. On a good-news day, which happens with probability $\alpha(1-\delta)$, informed traders who arrive with intensity μ will purchase the asset. Therefore, the buy and sell orders will arrive with intensities $\mu + \varepsilon_b$ (uninformed and informed buyers) and ε_s (uninformed sellers), respectively. On a bad-news day, which happens with probability $\alpha\delta$, informed traders who arrive with intensity μ will sell the asset. Thus, the buy and sell orders will arrive with intensities ε_b (uninformed buyers) and $\mu + \varepsilon_s$ (informed and uninformed sellers), respectively.

By imposing an independence structure across trading days, we obtain the following likelihood function for observations over I days:

$$L(\theta \mid M) = \prod_{i=1}^{I} L(\theta \mid B_i, S_i), \tag{7}$$

where (B_i, S_i) are trade data for day $i = 1, \ldots, I$. Maximizing the above likelihood function over the parameter space provides estimates of the structural parameters of the model. From the estimated model parameters, we can infer the unobservable private information arrivals through observed trade data. One variable of particular interest is the probability of informed trade (PIN), which represents a measure of information risk. This information risk variable is defined as

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b}, \tag{8}$$

where $\alpha\mu + \varepsilon_s + \varepsilon_b$ is the arrival rate of all trades and $\alpha\mu$ is the arrival rate of information-based trades. EHOH (2002) show that PIN has a significant positive effect on expected stock returns.

To apply the concept of PIN to the Treasury market, we need to interpret private information in the EHOH model broadly due to the different information structures of the stock and bond markets. In the stock market, private information is often viewed as inside information on a firm's cash flows. In the government bond market, macroeconomic variables such as fiscal deficits, inflation expectation, GDP growth, and money supply are the dominating factors that affect bond prices. As a result, private information in the Treasury bond market mainly arises from heterogeneous interpretation of public information and dealers' private access to customer order flows. Some traders may have an advantage in assessing how macroeconomic variables might affect bond prices due to their superior analytical skills. Also, dealers' observations of customer order flows provide important information for future price movements as excess buy or sell orders precede price increases or decreases, respectively. Furthermore, some individuals or institutions may even have limited private information in the traditional sense (see Brandt and Kavajecz, (2004)).[9] On the other hand, uninformed traders in the bond market could represent regular investors who do not have special skills in analyzing public information and cannot observe order flows. The aggregation of private information from various sources affects the mechanism of bond price changes. Because of the low transparency of the bond market, private information may not be incorporated into prices in a timely fashion. According to EHOH (2002), under these circumstances asymmetric information influences the price evolution process and affects the risk of holding the bond. Investors thus demand a premium for bearing the information risk.[10]

II. Estimation of Liquidity and Information Risks

A. The Data

We retrieve intraday U.S. Treasury security quotes and trades for all issues between January 1992 and December 2002 from the GovPX database for our empirical analysis.[11] We exclude September 2001 due to the unstable market

[9] Peiers (1997) and Ito, Lyons, and Melvin (1998) indicate that some large traders such as Deutsche Bank and Japanese banks are often perceived to be informed traders in foreign exchange markets.

[10] To adapt the EHOH model to the bond market, we can imagine the following scenario. Suppose some public news that is relevant to bond pricing arrives on the market on a certain day. The skilled investors can figure out whether the news will increase or decrease bond prices (they may not be correct in their inferences all the time, but they are more likely to be right than wrong). On the other hand, the unskilled investors may not be able to fully understand the implications of the news for bond prices (they are equally likely to be right or wrong with their inferences). As a result, the skilled (unskilled) investors would behave like informed (uninformed) traders in the original EHOH model. Likewise, the situation becomes very similar to that in the EHOH model if the news is due to the private observation of order flows.

[11] GovPX Inc. was set up under the guidance of the Public Securities Association as a joint venture by the primary dealers and several interdealer brokers in 1991 to increase public access to U.S. Treasury security prices. GovPX consolidates and posts real-time quotes and trades data from five of the six major interdealer brokers (Liberty, Tullett & Tokyo, Garban, ICAP, and Hilliard and Farber) during our sample period.

Table I

Summary Statistics of Treasury Data

This table reports means and standard deviations (in parentheses) of yield, net order flow, bid-ask spread in percentage, and quoted depth over the period January 1992 through December 2002 from the GovPX data set. Bonds are grouped by the remaining time to maturity and seasonedness, where seasonedness is separated into on-the-run and off-the-run.

	Remaining Time to Maturity					
Seasonedness	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years
			Yield (%)			
On-the-run	4.445	4.850	5.062	5.589	6.030	6.546
	(1.27)	(1.14)	(1.22)	(0.99)	(0.85)	(0.75)
Off-the-run	4.505	4.896	5.292	5.734	6.212	6.817
	(1.19)	(1.16)	(1.00)	(0.89)	(0.86)	(0.74)
			Net Order Flow ($Mil.)			
On-the-run	41.688	−27.566	110.133	144.436	100.810	17.591
	(322.67)	(324.79)	(503.85)	(427.82)	(293.09)	(103.84)
Off-the-run	27.252	53.931	75.533	43.036	4.751	0.637
	(92.17)	(54.18)	(53.09)	(31.41)	(22.82)	(25.01)
			Bid-Ask Spread (% of Midpoint Price)			
On-the-run	0.025	0.056	0.112	0.179	0.303	0.461
	(0.01)	(0.02)	(0.04)	(0.07)	(0.09)	(0.10)
Off-the-run	0.055	0.131	0.209	0.338	0.487	0.450
	(0.05)	(0.09)	(0.12)	(0.17)	(0.17)	(0.18)
			Quoted Depth ($Mil.)			
On-the-run	15.983	14.525	16.460	8.305	5.411	2.398
	(7.13)	(5.60)	(6.55)	(4.30)	(2.66)	(1.37)
Off-the-run	7.429	4.700	2.390	1.824	1.891	2.073
	(5.46)	(3.63)	(2.28)	(1.74)	(2.47)	(2.23)

conditions right after September 11. The GovPX data set contains detailed individual security information such as CUSIP, coupon, maturity date, and an indicator of whether the security is trading when issued, on the run, or off the run. The quote data include best bid and ask prices, the associated yields, the respective bid and ask size (depths), and the time of each bid and offer. The transaction data include the time, size, side (buy or sell), price (or yield), and cumulative volume. A unique feature of this data set is that the trade side or initiator is clearly indicated. Daily returns are calculated based on the midquote of the last trade for each day.

Table I reports the summary statistics of bond yield, net order flow, bid-ask spread, and depth. Bid-ask spread is the ask price minus the bid price divided by the midquote. Depth is the average of bid and ask sizes. Bonds are divided into six maturity categories by their remaining time to maturity: 0–6 months, 6–12 months, 1–2 years, 2–5 years, 5–10 years, and 10–30 years. In addition, bonds are separated by seasonedness into on-the-run and off-the-run groups. Within each category, we first obtain yields for each security and then average them across securities. As expected, bond yields increase with maturity. Net

Table II

Distribution of Bonds, Trades, and Volume over Sample Period

This table reports the distribution of number of bonds, number of trades, and trading volume across on-the-run and off-the-run categories in each year of our sample period. Volume is in million dollars.

Year	Seasonedness	Number of Bonds	Number of Trades	Trading Volume
1992	On-the run	114	501,732	4,239,401
	Off-the-run	322	287,050	2,140,014
1993	On-the run	112	549,033	4,991,157
	Off-the-run	314	196,214	1,789,294
1994	On-the-run	111	565,469	5,295,128
	Off-the-run	292	179,291	1,772,169
1995	On-the-run	110	617,095	5,392,367
	Off-the-run	276	165,843	1,602,841
1996	On-the-run	112	675,145	6,115,791
	Off-the-run	263	156,564	1,795,384
1997	On-the-run	111	677,401	6,545,807
	Off-the-run	248	142,257	1,738,848
1998	On-the-run	104	598,961	6,072,837
	Off-the-run	236	131,737	1,644,244
1999	On-the-run	92	365,109	3,607,744
	Off-the-run	211	97,478	1,268,199
2000	On-the-run	89	208,448	2,107,604
	Off-the-run	187	68,058	1,124,115
2001	On-the-run	87	72,213	1,067,506
	Off-the-run	171	33,091	701,590
2002	On-the-run	87	37,960	752,360
	Off-the-run	166	23,060	520,849

order flow is purchase minus sell volume. Net order flow is generally positive, indicating net purchases. Bid-ask spread also increases with maturity. The more liquid on-the-run issues tend to have lower yields and spreads, and higher net order flow and depths.

To achieve reliable parameter estimates of the EHOH model, we include only bonds that have at least 60 days of life remaining with at least one trade per day. Easley, et al. (1996) indicate that 60-day trade data will be sufficient for reliable PIN estimates while meeting the condition of stationarity. We do not include transactions associated with "when-issued" and cash management, or trades related to "workups." Our final sample contains 1,151 bonds, 7.1 million trades, and a total of $67.9 trillion trading volume.[12] Table II reports the distribution of the number of bonds and trades, and trading volume for both on- and off-the-run issues each year in our sample period. As expected, trading

[12] Even though we do not include "when-issued" transactions, our sample period is 22 months longer than Brandt and Kavajecz (2004); it turns out the total number of trades is very close to that in their sample.

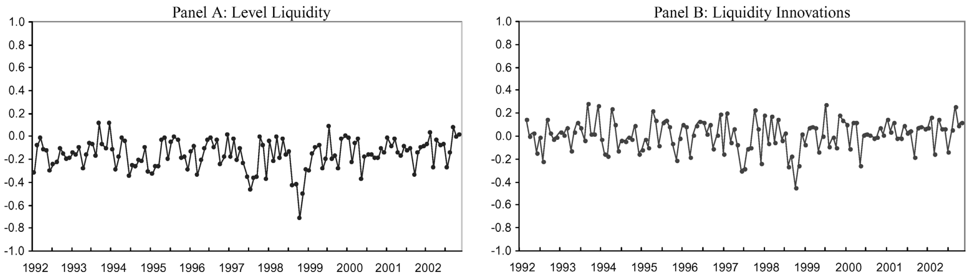

Figure 1. Aggregate Treasury market liquidity and innovations of liquidity. Panel A shows the time series of aggregate Treasury market liquidity. Panel B shows the innovations of Treasury market liquidity. Liquidity and its innovations are expressed in percentage terms on the vertical axis. We use the innovation series as the measure of marketwide liquidity to estimate systematic liquidity risk.

is concentrated on the on-the-run issues, which have more trades and higher trading volume. Number of trades and trading volume in the GovPX database declined significantly during the last 2 years of our sample.[13]

B. Estimation of Marketwide Liquidity of the Treasury Market

We construct the marketwide liquidity of the Treasury market ($\hat{\pi}_t$) in (2) by averaging individual bond liquidity measures estimated from the regression model in (1) month by month. Panel A of Figure 1 plots the level series of marketwide liquidity ($\hat{\pi}_t$) in percentage terms. Using the marketwide liquidity measure, we estimate liquidity innovations from the autoregression model in (3). Panel B of Figure 1 plots the scaled innovations of the marketwide liquidity measure (L_t) as defined in (4).

The liquidity measure $\hat{\pi}_t$ can be viewed as the cost of a trade with \$1 million. The mean (median) value of this liquidity measure is -0.16% (-0.14%) over the sample period. This indicates less than 0.2% cost for such a trade. The liquidity cost of Treasury bonds is considerably lower than that of stocks (2% to 3%) estimated by Pastor and Stambaugh (2003). This is not surprising given that the Treasury market is the most liquid market with the lowest transaction cost.

Though the innovations of marketwide liquidity (L_t) exhibit occasional downward spikes, the magnitude of these spikes is much milder than that for the stock market.[14] The largest downward spike occurs in October 1998 when the market was highly illiquid due to the episode involving Long-Term Capital

[13] The number of trades and quote records is considerably lower in the GovPX database for years 2001 and 2002. This is because the transaction volume of the electronic trading system increased substantially after 2001, causing the market share of the interdealer market to decline to only 20% to 30%, instead of two-thirds in our earlier sample period (see also Barclay, Hendershott, and Kotz (2006)).

[14] For example, the largest downward spike for aggregate liquidity has the value of $\hat{\pi}_t = -0.7\%$ for Treasury bonds (see Panel B, Figure 1), whereas in Pastor and Stambaugh's (2003) study the largest downward spike is about -47% and typical downward spikes range from -20 to -30%.

Management (LTCM). Other larger spikes are associated with the period surrounding the Asian financial crisis in 1997 and the stock market downturn in 2000.

Interestingly, the pattern of marketwide liquidity in Figure 1 resembles that reported by Fleming (2003). Over the sample period between December 30, 1996, and March 31, 2000, Fleming identifies significant spikes in Treasury market liquidity in October 1997, October 1998, and February 2000 using a comprehensive set of traditional liquidity measures such as bid-ask spread, trading volume, trading frequency, quote and trade size, price impact of trades, and on-/off-the-run yield spread.[15] These significant liquidity events are also captured by our marketwide liquidity index. Therefore, it appears that the Pastor–Stambaugh liquidity measure shares important fundamental information embedded in standard microstructure liquidity variables.

The empirical features of the liquidity innovations (L_t) in the Treasury market, however, are somewhat different from those in the stock market. The Treasury liquidity innovations have a negative correlation of -0.15 and -0.18 with the value-weighted stock return on all NYSE, Amex, and NASDAQ stocks and the equal-weighted returns on all Treasury securities in the GovPX database, respectively. The negative correlation between liquidity innovations and Treasury bond returns is likely due to the flight-to-quality phenomenon.[16] The correlation between the stock index return and the Treasury return is -0.34 over the entire sample period, indicating that the Treasury bond market often moves in the opposite direction of the stock market. When the stock market return is low, the Treasury bond return is high. Excess buy orders in the Treasury bond market during the stock market downturn increase liquidity cost. To understand the negative correlation between liquidity innovations and the stock market return, we calculate the correlations for the months with positive and negative returns more than 2%. The simple correlation between the liquidity measure and stock returns is 0.07 in positive-return months and -0.21 in negative-return months. Thus, it appears that the negative correlation between the liquidity measure and stock returns is primarily driven by stock market downturns. The correlation between liquidity innovations and the stock market return is stronger than those between liquidity innovations and other aggregate factors. For instance, correlations of liquidity innovations with SMB (size) and HML (value) are only 0.02 and 0.10, respectively.

The monthly liquidity innovations tend to be low when the Treasury bond market volatility is high. The correlation between L_t and the standard deviation of the Treasury market return is -0.08. This negative correlation suggests that the compensation required by dealers for a given level of order flow is somewhat larger when volatility is higher. The liquidity innovations are also negatively correlated with bid-ask spread (-0.21). This association is reasonable given that

[15] The February 2000 liquidity spike is attributed to the Treasury's Quarterly Refunding meeting, while the other two spikes are associated with the Asian and Russian financial crises in 1997 and 1998.

[16] Beber et al. (2007) show that the flight-to-quality effect is typically accompanied by a flight-to-liquidity effect where the liquidity effect is stronger during low market liquidity periods.

a higher spread corresponds to lower liquidity. The liquidity innovations are positively correlated with a monthly average order imbalance (0.11); a higher order imbalance thus contributes to higher liquidity cost. The innovation series appears to be serially independent. The autocorrelation of liquidity innovations is only 0.02.

To examine the robustness of our results, we consider alternative model specifications in constructing the marketwide liquidity measure. First, instead of using the return in excess of the Treasury market return, we construct two new liquidity measures by using the raw return or the return in excess of the Treasury bill rate in estimating the regression model in (1). We find that the two new liquidity measures fail to capture the major liquidity events during our sample period and the flight-to-quality effects. They also exhibit downward spikes in time periods that are not clearly associated with episodes of poor liquidity in financial markets. Second, instead of using the second-order autoregression in (3), we also consider time-series specifications at different lag orders.[17] We find that the estimation of the Treasury market liquidity is generally not sensitive to the lag order of the autoregression and that the second-order autoregression is the best specification according to the Akaike (1969) information criterion (AIC). Finally, we estimate the liquidity measure using the on-the-run and the off-the-run issues separately. We find that the liquidity measure of on-the-run issues is more volatile than that of off-the-run issues. Although the two liquidity measures exhibit similar patterns, they can diverge at times, and their correlation is only 0.33.[18]

In summary, our results show that the Pastor–Stambaugh liquidity measure captures a number of important liquidity episodes in the financial markets, and that the temporal pattern of the liquidity series is consistent with other liquidity measures based on traditional microstructure variables. We find that none of the alternative liquidity measures is as appealing as the Pastor–Stambaugh liquidity measure. Thus, the Pastor–Stambaugh method appears to work remarkably well for both the stock and the bond markets, and we adopt the Pastor-Stambaugh specification in (1) through (3) to estimate the liquidity series and systematic liquidity risk in the remainder of our analysis.

C. Estimation of the Trade Process and PIN

Next we provide empirical estimates for PIN as defined in (8). Using the daily numbers of buy and sell trades of individual bonds, we estimate the parameters of the EHOH model by maximizing the likelihood function in (7) over a 6-month period. The GovPX database provides the initiator of the trade, and thus there is no need to classify trade side using an algorithm (e.g., Lee and Ready (1991)) as in many equity market studies. The selection of the PIN estimation period

[17] The autoregressive model in (3), which can be rewritten as $\hat{\pi}_t = c + a\hat{\pi}_{t-1} + b\hat{\pi}_{t-2} + e_t$ ($a = 1 + a_1 + a_2$ and $b = -a_1$), is analogous to a second-order autoregression (AR(2)) in the level liquidity series.

[18] Details of these results are available from the authors upon request.

balances the need to have enough observations to obtain reliable parameter estimates and the need to allow flexibility in parameter estimates to capture variations in information flow over time. Treasury transaction data have a much shorter span. Transaction data are available for stocks since 1983, but transaction data records from GovPX only begin in 1992. While EHOH (2002) estimate their model for each stock in a 1-year period, we choose a 6-month period given our shorter sample period.

The trade process depends on five parameters. The first two parameters, (α, δ), are related to the daily information structure, and the last three parameters, (μ, ε_s, ε_b), are related to trade composition. The information on the first two parameters accumulates at a rate approximately equal to the square root of the number of trading days, whereas the information on the last three parameters accumulates at a rate approximately equal to the square root of the number of trade outcomes. This implies that the precision of μ, ε_s, and ε_b estimates will be greater than that of α and δ. Nevertheless, our sample size is large enough to provide sufficient precision for estimates of each parameter. Indeed, all parameter estimates are estimated with high precision and are very stable over time.

Table III summarizes the parameter estimates. The small standard errors in the last column of Panel A indicate strong statistical significance for all parameter estimates. The mean (median) probability of an information event α is 0.27 (0.23). The probability of bad news is generally lower than that of good news over our sample period. The mean (median) δ is 0.39 (0.35), which is lower than the probability of good news. This may reflect that interest rates were more often falling and bond prices rising over our sample period. The results are consistent with the predominantly positive net order flows in Table I. The mean (median) arrival rate of uninformed buy orders $\varepsilon_b$is slightly higher than that of uninformed sell orders ε_s. PIN is computed using the semi-annual estimates of α, δ, μ, ε_s, and ε_b. The mean (median) PIN estimate is 0.26 (0.27).

In Panel B of Table III, we first report the estimates of α for on- and off-the-run issues with different maturities for all trading days. As shown, α estimates are much higher for on-the-run bonds across all maturities. Since informed traders tend to concentrate on on-the-run issues, their trades respond to new information more efficiently and result in higher α estimates. For the same reason, the α estimates for on-the-run issues should better represent the true probability of new information arrival to the market. The α estimates vary somewhat across maturities (from 3 months to 30 years) and are highest for the 5-year on-the-run issue, which is the most frequently traded Treasury security. Brandt, Kavajecz, and Underwood (2007) provide corroborative evidence that trading of the 5-year bond contributes more to price discovery of the Treasury market and informed traders are more likely to trade in this market segment.

Given that a main source of asymmetric information in the Treasury bond market is heterogeneous interpretation of macroeconomic news, we also report estimates of α for trading days with/without macroeconomic announcements in Panel B of Table III. Specifically, we divide the sample into days with and without macroeconomic announcements and obtain α estimates for each subsample

Table III

Summary Statistics of Parameter Estimates of the Trade Model

Panel A in this table contains means, medians, standard deviations, and median standard errors for the parameters estimated from the likelihood estimation in (7). α is the probability of an information event, δ is the probability of a low signal (bad news), μ is the rate of informed trade arrival, ε_b is the arrival rate of uninformed buy orders, and ε_s is the arrival rate of uninformed sell orders. PIN is the probability of informed trading as given by $PIN = \frac{\alpha\mu}{\alpha\mu+\varepsilon_s+\varepsilon_b}$. Panel B reports the estimates of α by seasonedness and maturity (from 3 months to 30 years) for all trading days and days with/without macroeconomic announcements.

Panel A. Summary Statistics of Parameters of the Trade Model

Variable	Mean	Median	Standard Deviation	Median Standard Error
α	0.2684	0.2309	0.1707	0.0387
δ	0.3866	0.3479	0.2605	0.0727
μ	12.2077	7.8853	12.1146	0.9737
ε_b	3.4946	2.7706	3.2278	0.4951
ε_s	3.3190	2.5212	3.4743	0.1011
PIN	0.2619	0.2652	0.0592	0.0147

Panel B. Distribution of α Parameters by Maturity and Seasonedness for All Trading Days and Days with/without Macroeconomic News

Seasonedness/ Maturity	3M	6M	1Y	2Y	3Y	5Y	7Y	10Y	30Y	All
					α for all trading days					
On-the-run	0.4381	0.4306	0.4176	0.4046	0.4132	0.4564	0.3873	0.4155	0.4237	0.4098
Off-the-run	0.2122	0.2089	0.2205	0.2127	0.1642	0.1908	0.1821	0.1546	0.1810	0.1964
					α for days with macroeconomic news					
On-the-run	0.4641	0.4494	0.4700	0.4777	0.4673	0.4758	0.4300	0.4774	0.4434	0.4650
Off-the-run	0.2410	0.2382	0.2575	0.2502	0.2410	0.2186	0.2347	0.2337	0.2544	0.2463
					α for days without macroeconomic news					
On-the-run	0.3827	0.3813	0.3794	0.3891	0.3892	0.3926	0.3872	0.3899	0.3849	0.3861
Off-the-run	0.1757	0.1659	0.1736	0.1398	0.1591	0.1553	0.1694	0.1521	0.1629	0.1651

based on macroeconomic announcements collected from Bloomberg between January 1992 and December 2002.[19] The mean values of α across all on-the-run issues are 0.47 and 0.39 for days with and without a news announcement, respectively. A similar pattern is also found for off-the-run issues with mean α values of 0.25 and 0.17 for days with and without a news announcement, respectively. Consistent with our conjecture, α tends to be higher on trading days with news announcements.

However, the estimates of α are much smaller than the frequency of macroeconomic announcements during our sample period. We find 1,814 days with at

[19] We supplement the Bloomberg data by the macroeconomic announcements in "The Week Ahead" section of *Business Week*. Macroeconomic news is released regularly in a "lock-up" condition to ensure that the information is released to the public at scheduled times. News is mostly released at 8:30 a.m., 9:15 a.m., 10 a.m., 2 p.m., 3 p.m. or 4:30 p.m.

least one macroeconomic news announcement, which represents about 65% of the total trading days in our sample.[20] On the other hand, the mean of α across all Treasury issues is only 0.27, and even the mean of α of all on-the-run issues is only 0.41. There are two possible reasons for these discrepancies. First, not all macroeconomic news announcements represent new information because some of these announcements are already anticipated by market participants. Thus, a macroeconomic news announcement day is not necessarily a new information event day. Second, α represents the arrival rate of private information. A macroeconomic news announcement need not induce asymmetric information even though it is unanticipated, if the information release does not cause a disagreement among investors about security value or does not result in private information gathering by informed traders.

Summarizing, we find that parameter estimates of the informed trading model are quite stable and individual parameters are estimated with high precision. The values of estimated parameters are sensible and generally consistent with the pattern of scheduled macroeconomic announcements.

D. Does PIN Capture Informed Trading in the Treasury Market?

Before including PIN in asset pricing tests, we examine whether our PIN estimates are consistent with the predictions of microstructure theories (e.g., Admati and Pfleiderer (1988)) that informed trading should take place in segments of markets with high liquidity and low transaction cost to minimize price impacts and trading costs. More specifically, we test whether bonds with higher liquidity, greater depth, and lower spread tend to have higher PIN estimates.

We divide all bonds in our portfolio into three groups along each of the following key bond characteristics: seasonedness, time to maturity, spread, and depth. For seasonedness, we consider near-the-run (group 1), off-the-run (group 2), and very-off-the-run (group 3) issues. Since our PIN is estimated in a 6-month period, we refer to bonds that have once been classified as on-the-run within the 6-month PIN estimation period as near-the-run issues. Bonds that have been issued for more than 5 years are classified as very-off-the-run issues. The remaining bond issues are classified as off-the-run issues. With respect to maturity, short-, medium-, and long-maturity bonds are defined as bonds with maturity less than 1 year, between 1 to 5 years, and longer than 5 years, respectively. For spread and depth, we rank all bonds by their average spread and depth and divide them into three groups of equal size with low, medium, and high values of the two variables.

To compare the values of PIN across different bond groups, we conduct the Kruskal–Wallis test and the Wilcoxon rank-sum test. The Kruskal–Wallis test determines whether PIN values for all three groups are drawn from the same population. The null hypothesis of identical populations is rejected if one or

[20] This ratio is quite close to the figure (65.2%) reported by Fleming and Remolona (1999), which covers a much shorter period (250 trading days). The frequency is quite stable over different sample periods since macroeconomic news announcements are scheduled regularly.

Table IV

Nonparametric Tests of PIN for Different Bond Groups

Treasury bonds are classified into low, high, and medium groups based on their run status (seasonedness), maturity, spread, and depth. For the RUN groups, we have near-the-run (group 1), off-the-run (group 2), and very-off-the-run (group 3). Near-the-run includes the bonds that have been once on the run within the past 6 months. Off-the-run includes bond issues that have been off the run for 2 to 5 years, and very-off-the-run includes bond issues that have been off the run for more than 5 years. For the remaining groupings, groups 1, 2, and 3 correspond to low, medium, and high values of the criterion variables. For maturity groups, low-maturity includes bonds with maturity less than 1 year, medium-maturity includes bonds with maturity between 1 to 5 years, and high-maturity includes bonds with maturity greater than 5 years. For both spread and depth groups, we rank all bonds based on daily average spread and depth, and divide them into low, medium, and high groups. Depth is the average of bid and ask size. Panel A presents Kruskal–Wallis tests on PIN. The Kruskal–Wallis statistic is employed to test the null hypothesis that PIN values for all three groups in RUN, maturity, spread, and depth are drawn from the same populations versus the alternative hypothesis that at least one of the populations is different from other populations. Reported are test statistics and p-values (in parentheses). Panel B presents pairwise Wilcoxon Rank-Sum tests on PIN. The Wilcoxon Rank-Sum statistic is employed to test the null hypothesis that two sample groups are drawn from identical populations against the alternative that one population has a higher PIN value. Groups 1, 2, and 3, classified based on the seasonedness, include the near-the-run, off-the-run, and very-off-the-run bonds defined in Panel A. Groups 1, 2, and 3 of the remaining groupings include low, medium, and high maturities, spreads, and depths. Reported are test statistics and p-values (in parentheses).

Panel A. Kruskal–Wallis Tests on PIN

RUN	Maturity	Spread	Depth
40.57	121.51	130.94	163.79
(0.0001)	(0.0001)	(0.0001)	(0.0001)

Panel B. Pairwise Wilcoxon Rank-Sum Tests on PIN

Category	Group 1 to 2	Group 1 to 3	Group 2 to 3
RUN	5.6411	3.8818	1.7102
	(0.0001)	(0.0001)	(0.0872)
Maturity	10.9664	4.5519	1.2954
	(0.0001)	(0.0001)	(0.1952)
Spread	10.4400	7.1600	−0.2198
	(0.0001)	(0.0010)	(0.8260)
Depth	2.1396	−6.1273	−12.4626
	(0.0324)	(0.0001)	(0.0001)

more population distributions differ from the others. The Kruskal–Wallis test statistics and p-values are reported in Panel A of Table IV. The Wilcoxon rank-sum statistic tests the null hypothesis that two sample groups are drawn from identical populations against the alternative that one population has a higher PIN value. These test statistics and p-values are reported in Panel B of Table IV.

Figure 2 displays the cumulative distributions of PIN for each grouping based on seasonedness, maturity, spread, and depth, respectively. Panel A shows that more liquid issues have higher PIN. That is, near-the-run issues have a higher

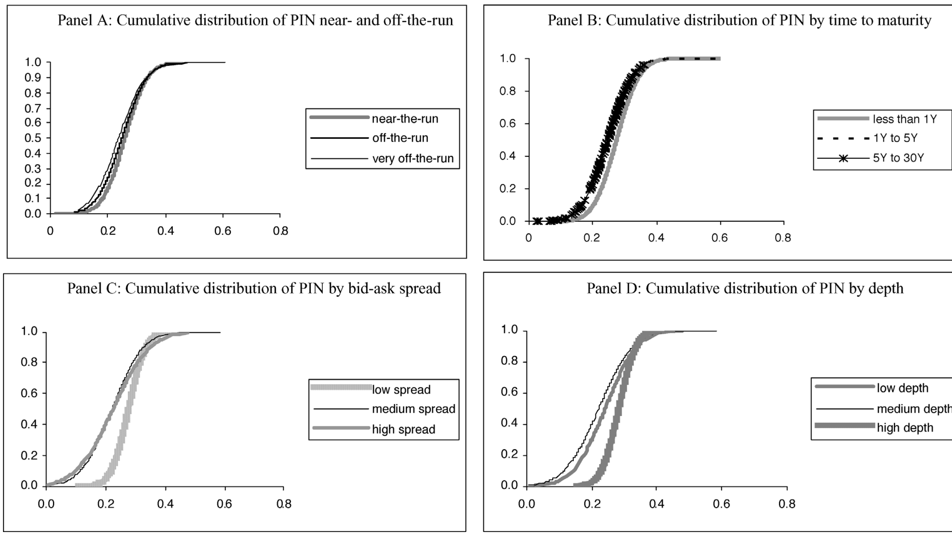

Figure 2. Cumulative distribution of the probability of information-based trading by bond groups. The vertical axis displays the cumulative probability while the horizontal axis represents the probability of information-based trading (PIN). Panel A displays the cumulative distribution of PIN for bonds that are near-the-run, off-the-run, and very-off-the-run (more than 5 years after issuance). Panel B displays the cumulative distribution for bonds with maturity less than 1 year, 1–5 years, and greater than 5 years. Panel C displays the cumulative distribution of the probability of PIN for low-, medium-, and high-spread groups. Panel D displays the cumulative distribution of PIN for low-, medium-, and high-depth groups.

PIN than off-the-run issues, which in turn have a higher PIN than the very-off-the-run issues. The Kruskal–Wallis statistic (see Panel A of Table IV) strongly rejects the hypothesis that the population distributions are the same for the three groups. Pairwise testing based on the Wilcoxon rank-sum test (Panel B of Table IV) shows that the cumulative probability function of the near-the-run issues is significantly below those of off-the-run and very-off-the-run issues, whereas the cumulative probability distribution of off-the-run issues is only significantly below that of very-off-the-run issues at the 10% level. These results show that informed traders prefer more liquid bonds for their trading.

Panel B of Figure 2 shows that PIN is higher for shorter-maturity bonds. The Kruskal–Wallis statistic again strongly rejects the null hypothesis that the distributions are the same for the three maturity groups. Wilcoxon rank-sum tests show that the cumulative probability distribution function of the shortest maturity is significantly below those of the medium- and long-maturity groups. By contrast, the difference in the cumulative probability distribution functions is not significant between the medium- and long-maturity groups.

Panel C shows that the cumulative distribution function of the low-spread group lies below those of the medium- and high-spread groups. The Kruskal–Wallis statistic rejects the null that distributions are the same for all groups. The Wilcoxon rank-sum tests show that PIN is higher for the low-spread bonds.

However, PIN is not significantly different between the medium- and high-spread bonds.

Panel D of Figure 2 shows that the cumulative probability distribution function of the high-depth bonds lies below that of low- and medium-depth bonds. The Kruskal–Wallis statistic rejects the null of equal distributions. The Wilcoxon rank-sum tests show that the cumulative probability distribution function of the high-depth bonds is significantly below those of the low- and medium-depth bonds at the 1% level. Although the cumulative probability distribution function of the low-depth bonds is below that of the medium-depth bonds, the difference between these two groups is relatively small in an economic sense compared to the high-depth group.

The above results show that consistent with the predictions of microstructure theories, PIN estimates appear to be higher for high-liquidity, short-maturity, low-spread, and high-depth bonds. Overall, PIN seems to capture information-based trading of different Treasury securities quite well.

III. Liquidity and Information Risks and Expected Treasury Returns

A. Methodology

In this section, we provide cross-sectional analysis on the relation between expected Treasury bond returns and liquidity and information risks measured by β_L and PIN, respectively. One challenge we face in our analysis is that in contrast to the vast literature on cross-sectional stock returns, there is little work on the cross-section of bond returns. Fama and French (1993) study the common factors in stock and bond returns and find that in addition to the three Fama–French factors, two-term structure factors (the term premium and the default premium) capture most of the variation in the returns of bond portfolios in their sample. In a more recent study, Gebhardt, Hvidkjaer, and Swaminathan (2005) use these two-term structure factors and individual bond characteristics to explain the cross-section of expected corporate bond returns.

In our empirical investigation, we follow these two studies by including both systematic risk factors and bond characteristics as explanatory variables for the cross-section of Treasury returns. To the extent that the market, size, and book-to-market factors capture systematic risks and the stock and bond markets are integrated, these equity market factors may share common variations in government bond returns. While we include the term premium in our regression, we do not include the default premium because Treasury securities have no default risk. To control for any risks not captured by the above systematic risk factors, we also include bond characteristics, such as time to maturity and seasonedness. Later we check the robustness of our results by including other liquidity and information proxies, such as spread, volatility, abnormal volume, order imbalance, and depth.

In our base model, we estimate the following cross-sectional regression for each month:

Table V

Distribution of Bonds over Maturities

This table shows the distribution of bonds over maturities. We report the average percentage of the bonds with maturity within the given interval for each year in our sample period. We form 11 maturity portfolios based on these maturity categories.

	Maturity										
Year	0–3M	3–6M	6–9M	9–12M	1–1.5Y	1.5–2Y	2–3Y	3–4Y	4–5Y	5–10Y	>10Y
1992	4.24	3.45	2.33	4.68	4.55	11.58	11.46	2.33	22.46	26.98	5.94
1993	11.50	10.80	5.52	6.43	8.50	7.29	8.91	11.82	12.14	15.68	1.41
1994	13.08	12.34	6.70	6.44	7.92	7.92	10.54	12.18	12.50	8.83	1.55
1995	14.75	12.19	8.26	8.47	10.50	10.17	12.38	9.22	9.32	3.14	1.59
1996	17.39	16.67	9.26	9.62	12.40	11.90	13.75	3.34	3.01	1.69	1.81
1997	19.08	15.85	9.93	10.05	13.16	12.32	13.79	1.54	2.04	1.83	1.22
1998	17.59	16.61	9.86	9.24	14.20	11.32	14.46	2.78	1.68	1.16	1.19
1999	20.62	17.43	8.96	9.75	11.69	13.00	13.93	2.09	0.00	1.42	1.39
2000	26.08	21.24	11.53	10.90	13.18	11.31	0.00	0.00	1.87	1.95	1.94
2001	23.29	18.69	10.84	17.12	9.18	0.00	0.00	0.00	14.80	3.51	2.72
2002	34.00	28.51	17.76	14.27	0.00	0.00	0.00	0.00	6.20	0.00	0.00

$$\begin{aligned} R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}\beta_{iMKT} + \gamma_{2t}\beta_{iSMB} + \gamma_{3t}\beta_{iHML} + \gamma_{4t}\beta_{iTerm} + \gamma_{5t}\beta_{iL} \\ + \gamma_{6t}PIN_{it-1} + \gamma_{7t}TM_{it} + \gamma_{8t}RUN_{it} + \gamma_{9t}Flag_{it} + \eta_{it}, \end{aligned} \tag{9}$$

where R_{it} is the return on bond i in month t; R_{ft} is the 1-month Treasury bill rate; $\beta_{ik}, k = MKT, SMB, HML, Term$, and L are the systematic risks of bond returns associated with the market returns, size, book-to-market, term premium, and liquidity factors, respectively; PIN_{it-1} is the probability of information-based trading; TM_{it} is time to maturity; RUN_{it} is a dummy variable indicating whether the bond is on- or off-the-run in month t; $Flag_{it}$ is a dummy variable that is equal to 1 for Treasury notes or bonds in the month immediately after these securities go off the run; γ_{jt}, $j = 0, \ldots, 9$ are the parameters to be estimated; and η_{it} is the error term.

The betas of the systematic risk factors in the above cross-sectional regression are estimated using a portfolio approach. This is mainly because bond maturity changes over time, and after a few years a long-term bond becomes a short-term bond. In addition, Treasury bills have short maturities, which render regression over a long estimation period infeasible. Therefore, we construct equally weighted portfolios based on bond maturities. The GovPX database contains more short-term bonds than long-term bonds, particularly in the last 3 years of the sample period (see the distribution in Table V). We choose the following portfolio categories: 0–3, 3–6, 6–9, 9–12 months, 1–1.5, 1.5–2, 2–3, 3–4, 4–5, 5–10, and 10–30 years.[21] We widen the maturity range of the last two

[21] We reach very similar conclusions using 19 portfolios with the following maturity categories: 0–3, 3–6, 6–9, 9–12 months, 1–1.5, 1.5–2, 2–3, 3–4, 4–5, 5–6, 6–8, 8–10, 10–12, 12–14, 14–16, 16–18, 18–20, 20–25, and 25–30 years. These results are available from the authors upon request.

portfolios because there are fewer bonds in these categories (see also Fama and French (1993) and Brandt and Kavajecz (2004) for similar grouping). The portfolios are updated monthly because the maturity of the bond changes over time and some bonds may mature in a given month. We estimate the betas using the time-series regression model in (5) for each of these 11 portfolios based on the previous 3 years of monthly returns.[22] In the month immediately following the estimation period, each beta is assigned to each bond in the portfolio to perform cross-sectional regression tests. For example, for each month in a given year, if an individual bond has a maturity of 1.25 years, we will use the beta of the portfolio with maturity 1 to 1.5 years, estimated in the preceding estimation period, as the explanatory variables in the cross-sectional regression for that particular month. Because the maturity portfolio compositions may change each month, individual bond betas also may change each month.

The dummy variable Flag captures the effect on the required return of a bond that goes off the run in the month immediately after a similar new issue is auctioned. Previous studies show that on-the-run Treasuries command a price premium over the more seasoned Treasuries for reasons such as liquidity, transaction cost, and repo specialness. Krishnamurthy (2002) shows that higher demand by buy-and-hold investors for more liquid on-the-run Treasuries bids up their price in the cash market. Graveline and McBrady (2006) show that on-the-run Treasuries carry a price premium because it is easier to locate more liquid on-the-run Treasuries to close out a short-sell position associated with interest rate risk hedging. Therefore, the price of existing on-the-run Treasuries may suddenly drop when they become off the run after new Treasuries are auctioned. Goldreich, Hanke, and Nath (2005), however, argue that both current and expected future benefits of liquidity are already reflected in the current market price, and, as a result, the auction of new Treasuries may not have a significant impact on the price or expected return of the current long-term on-the-run securities. These studies focus on another aspect of liquidity risk, where liquidity may be low when investors have a need to liquidate their positions or cover their short positions. The Flag dummy variable controls for this type of liquidity effect on the expected return of those Treasuries that go off the run.

Parameters estimated from cross-sectional regressions are averaged over time following the Fama and MacBeth (1973) methodology. However, Litzenberger and Ramaswamy (1979) note that this procedure is inefficient under time-varying volatility. Thus, we also employ their technique, which is essentially a weighted least square method, to correct this inefficiency. This method weights the coefficients by the inverse of their volatility when summing across the cross-sectional regressions. We report both the Fama–MacBeth and Litzenberger–Ramaswamy coefficients and test statistics in cross-sectional regressions.

[22] For each monthly cross-sectional test beginning from January 1995, we use the previous 3 years of monthly returns to estimate betas. For each month from January 1993 to December 1994, we use all the observations from the beginning of our sample, that is, January 1992, to the month right before a cross-sectional test month to estimate betas.

Of primary interest are the coefficients on liquidity risk, β_L, and PIN in the cross-sectional regression. Our hypothesis is that the market should compensate bond investors for bearing liquidity and information risks. That is, the time-series average of γ_5 and γ_6 in the cross-sectional regressions of (9) should be significantly positive, or higher liquidity and information risks should translate into a higher required rate of return for government bonds.

B. Empirical Results on Expected Bond Returns

In this section, we provide empirical results on the relation between expected Treasury bond returns and measures of liquidity and information risks. We first report results from the base model in (9), which uses the stock market return as the market return and the Treasury bond liquidity factor as marketwide liquidity. We then report results based on alternative measures of marketwide liquidity and market returns.

B.1. Results of the Base Model

Panel A of Table VI provides descriptive statistics for the variables used in the cross-sectional regression. The mean stock market return beta is about 0.08, which is small but in line with the findings in Fama and French (1993). The mean SMB beta is negative, and the mean HML, TERM, and liquidity betas are positive.[23] The mean time to maturity is 2.4 years, indicating that the sample is tilted toward shorter-term bonds. The average daily bid-ask spread is 2.36 basis points. The mean standard deviation (STD) of daily returns is 0.12, which is considerably lower than that of stocks. Abnormal volume (Ab_Vol) is the percentage of deviations of the dollar volume in a given year from the average dollar volume for the entire sample period for each maturity portfolio. This variable is used later in the specification tests of the cross-sectional model to control for volume effect. Order imbalance (IMB) is the difference between purchase and sell volumes divided by the total purchase and sell volume (in dollar terms). Daily average of order imbalance is used as an alternative information variable later in the cross-sectional regressions. The market quality index (MQI) of Bollen and Whaley (1998) is defined as the ratio of average quoted depth to the percentage bid-ask spread, where quoted depth is the average of bid and ask quote sizes (in million dollars). In addition to return volatility, we calculate volatility of bid-ask spreads (STDS). As shown, spread volatility is much lower than return volatility.

Panel B of Table VI presents the simple bivariate correlations computed from monthly data. Systematic liquidity risk (β_L) is positively correlated with bid-ask spread, volatilities of returns and spreads, abnormal volume, and order imbalance, and is negatively correlated with MQI. This finding is consistent with Acharya and Pedersen (2005) and suggests that illiquid Treasuries also

[23] We multiply the liquidity beta by 10, or reduce the scale factor in (4) to 100, to bring it to a comparable level.

Table VI

Summary Statistics of Cross-sectional Regression Variables

This table contains summary statistics for the variables included in asset pricing tests. All statistics are calculated by pooling all months. *Return* is the percentage monthly return in excess of the 1-month T-bill rate. β_{MKT}, β_{SMB}, β_{HML}, β_{TERM}, and β_L are portfolio betas of equity market returns, size, book-to-market, term premium, and market liquidity estimated from the returns of 19 maturity portfolios. *PIN* is the probability of informed trading estimated every 6 months for each bond. *Spread* is the yearly average daily bid-ask spread (in percentage), *STD* (*STDS*) is the standard deviation of daily returns (spread), and *Ab_Vol* is the abnormal trading volume in the past year. The abnormal trading volume is the difference between the volume in the past year and the average volume over the entire sample period divided by the sample average volume. Order imbalance is the difference between purchase and sell orders divided by the total purchase and sell orders. The *IMB* variable is the average daily order imbalance in the past year. *MQI* is defined as the ratio of average quoted depth to percentage bid-ask spread, where quoted depth is the average of bid and ask quote sizes. Panel A presents the descriptive statistics used in the asset pricing tests. Panel B presents the correlation matrix of the correlations of the variables used in the asset pricing tests.

Panel A. Descriptive Statistics

Variable	Mean	Median	Minimum	Maximum	Std Deviation
Return	0.1236	0.1431	−0.7088	1.5224	0.4292
β_{MKT}	0.0821	0.0375	−0.0681	0.2905	0.1052
β_{SMB}	−0.0297	−0.0205	−0.1349	0.0375	0.0398
β_{HML}	0.0681	0.0446	−0.0024	0.2246	0.0694
β_{TERM}	0.6549	0.2419	−1.4920	3.4405	1.1251
β_L	0.6636	0.3201	−0.0080	2.8445	0.8060
TM	2.4135	1.3764	0.0306	30.1653	3.9064
PIN	0.2619	0.2652	0.0000	0.6963	0.0650
Spread	0.0236	0.0188	0.0006	0.1038	0.0171
STD	0.1167	0.0785	0.0048	0.4967	0.1012
IMB	0.0715	0.0719	−0.4590	0.4983	0.0894
Ab_Vol	0.2567	0.2992	−0.9363	1.1822	0.3321
MQI	0.1048	0.1287	0.0023	0.3115	0.2158
STDS	0.0204	0.0169	0.0007	0.1702	0.0159

(continued)

Table VI—*Continued*

Panel B. Correlation Matrix

	β_{MKT}	β_{SMB}	β_{HML}	β_{TERM}	β_L	*TM*	*PIN*	*Spread*	*STD*	*Ab_Vol*	*IMB*	*MQI*	*STDS*
Return	0.0174	0.0758	0.1919	0.2519	0.2804	0.1579	−0.0339	0.2063	0.1870	0.1205	0.0174	−0.0927	0.1803
β_{MKT}		−0.7189	0.7367	−0.1608	0.2466	0.3456	−0.1477	0.5700	0.6414	0.4829	−0.0271	−0.2784	0.3834
β_{SMB}			−0.3125	0.3248	0.1366	−0.0940	0.1207	−0.1789	−0.3037	−0.3665	−0.0095	0.1536	−0.0781
β_{HML}				0.2042	0.6657	0.5373	−0.1440	0.8212	0.8260	0.4882	−0.0469	−0.3492	0.6264
β_{TERM}					0.6167	0.1999	−0.0384	0.4004	0.2713	−0.0076	0.0451	−0.1542	0.3738
β_L						0.4047	−0.0875	0.7357	0.6409	0.2733	0.0131	−0.2822	0.5986
TM							−0.0736	0.6869	0.7562	0.1935	−0.0954	−0.2206	0.5934
PIN								−0.1145	−0.1390	−0.0431	0.0023	0.1301	−0.0640
Spread									0.9100	0.4094	−0.0461	−0.4386	0.8403
STD										0.3560	−0.0919	−0.3794	0.7272
Ab_Vol											−0.1003	−0.1352	−0.0404
IMB												−0.1798	0.2894
MQI													−0.4500

have high liquidity risk. The correlations between PIN and the rest of the explanatory variables are low. PIN is negatively correlated with time to maturity and market, book-to-market, term, and liquidity betas, but these correlation coefficients are small. Returns are positively correlated with the market, size, book-to-market, term, and liquidity betas. Time to maturity is positively correlated with spread, volatility, and the market, book-to-market, and liquidity betas but negatively related to the size beta. Volatility of returns is positively correlated with spread, time to maturity, and the market return and book-to-market betas. Volatility of spreads is positively correlated with volatility of returns and bid-ask spread and in general, its correlation pattern is similar to return volatility. MQI is negatively correlated with the liquidity, market, book-to-market, and term betas, and with spread and return volatility.

Table VII reports the results of the cross-sectional regressions for the base model. Panel A shows the results for the Fama–MacBeth regressions while the results in Panel B correspond to the Litzenberger–Ramaswamy regressions. As shown, the Litzenberger–Ramaswamy weighted least square method tends to produce greater efficiency. The first row in each panel reports the results for the base model in which the stock market return represents the market return, and the Treasury bond market liquidity factor represents the marketwide liquidity. The results show that information and liquidity risks are priced. The coefficient on liquidity beta is positive and significant for both the Fama–MacBeth and Litzenberger–Ramaswamy regressions. The coefficient (0.0741) on systematic liquidity risk in the Fama–MacBeth regression multiplied by the mean value of β_L (0.6636) gives a predicted monthly excess return of 4.92 basis points, which explains about 40% of mean monthly excess returns of Treasury bonds (12.36 basis points). Thus, a substantial proportion of Treasury return is explained by the Pastor–Stambaugh liquidity beta. Based on the point estimate of β_L, a difference of 10 percentage points in β_L between two bonds results in a difference in required return of 0.74 basis points per month, which accounts for 6% of the mean excess return of Treasury bonds. This is an economically meaningful and significant difference. The effect of liquidity risk is even more impressive if we consider the transaction size of Treasuries. The average interdealer trade size of Treasuries is about 10 million per trade. This further translates into a sizable liquidity premium per trade in dollar terms.

The coefficient on PIN is also positive and significant in both the Fama–MacBeth and Litzenberger–Ramaswamy regressions. The coefficient (0.0502) on PIN in the Fama–MacBeth regression multiplied by its mean value (0.2619) gives a predicted monthly excess return of 1.31 basis points, which explains about 11% of mean monthly excess returns of Treasury bonds. The point estimate on the PIN coefficient indicates that a difference of 10 percentage points in PIN between two bonds results in a difference in required return of 0.5 basis points per month. This amounts to 4% of the mean excess return of Treasury bonds per month. Again, this magnitude is economically significant, and even more so when trade size is taken into account.

Besides the liquidity and information risks, time to maturity is significant in both the Fama–MacBeth and Litzenberger–Ramaswamy regressions. The

Table VII

Asset Pricing Tests

This table contains time-series averages of the coefficients in cross-sectional asset pricing tests using the standard Fama and MacBeth (1973) methodology and Litzenberger and Ramaswamy (1979) precision-weighted means (weighted least squares (WLS)). The dependent variable is the percentage monthly return in excess of the 1-month T-bill rate. β_{MKT}, β_{SMB}, β_{HML}, β_{TERM}, and β_L are betas of market returns, size, book-to-market, term premium, and market liquidity. *PIN* is the probability of information-based trading estimated from the preceding 6-month period for each bond, and *TM* is time to maturity. *RUN* is the dummy variable indicating whether the bond is on-the-run or off-the-run. The value of the dummy variable equals 1 if the bond is on-the-run and 0, otherwise. Flag is the dummy variable that equals 1 for notes and bonds in the month immediately after these securities go off the run, and 0 for other months. We estimate market betas using both stock market and broad market returns, and estimate liquidity betas using the Pastor–Stambaugh Treasury bond (TB), stock, and broad market liquidity indexes, respectively. Broad market returns are value-weighted returns of equity, corporate bond, and Treasury market returns. The broad market liquidity index is a simple average of Treasury bond and stock market liquidity indexes. Student's t-values are given in parentheses.

Panel A. Fama–MacBeth Regressions

		Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{TERM}	β_L	*PIN*	*TM*	*RUN*	*Flag*	R^2
Stock	P&S TB	0.0217	1.0802	0.6411	0.5099	0.0298	0.0741	0.0502	0.0422	−0.0173	0.0077	0.8192
Market	Liquidity	(2.74)	(1.47)	(0.68)	(0.74)	(2.77)	(2.46)	(2.71)	(3.24)	(−1.86)	(2.24)	
Return	P&S Stock	0.0423	1.5783	0.8950	0.8978	0.0058	0.0200	0.0516	0.0296	−0.0046	0.0063	0.8170
	Liquidity	(5.05)	(1.72)	(0.82)	(1.33)	(0.43)	(1.99)	(2.71)	(2.37)	(−0.75)	(2.21)	
	Broad Market	0.0489	1.3540	0.8456	0.8461	0.0047	0.0294	0.0634	0.0263	−0.0094	0.0059	0.8161
	Liquidity	(5.91)	(1.45)	(0.73)	(0.94)	(0.35)	(2.22)	(3.31)	(2.07)	(−1.37)	(1.09)	
Broad	P&S TB	0.0307	0.1573	1.1256	0.9848	0.0427	0.0547	0.0316	0.0342	−0.0083	0.0106	0.8164
Market	Liquidity	(3.83)	(2.08)	(0.94)	(1.13)	(1.97)	(2.99)	(2.59)	(3.16)	(−1.24)	(2.16)	
Return	P&S Stock	0.0335	0.1714	0.8206	0.8597	0.0230	0.0115	0.0416	0.0377	−0.0109	0.0096	0.8149
	Liquidity	(4.50)	(2.48)	(0.93)	(1.05)	(1.32)	(1.33)	(2.11)	(3.44)	(−1.31)	(1.08)	
	Broad Market	0.0286	0.1699	0.4143	0.4099	0.0348	0.0179	0.0497	0.0369	−0.0041	−0.0009	0.8133
	Liquidity	(3.74)	(2.69)	(0.42)	(0.46)	(2.01)	(2.07)	(2.73)	(3.47)	(−0.70)	(−0.16)	

(continued)

Table VII—*Continued*

Panel B. Litzenberger–Ramaswamy WLS Regressions

		Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{TERM}	β_L	*PIN*	*TM*	*RUN*	*Flag*	R^2
Stock	P&S TB	0.0164	0.9745	0.5839	0.7728	0.0158	0.0651	0.0366	0.0279	−0.0113	0.0061	0.8192
Market	Liquidity	(5.94)	(10.16)	(4.40)	(5.56)	(5.71)	(9.16)	(4.08)	(17.45)	(−6.45)	(2.22)	
Return	P&S Stock	0.0292	0.8023	0.3253	0.4856	0.0126	0.0070	0.0310	0.0216	−0.0059	0.0030	0.8170
	Liquidity	(10.05)	(10.13)	(3.22)	(4.30)	(6.70)	(6.94)	(3.35)	(12.83)	(−3.32)	(1.03)	
	Broad Market	0.0347	0.9112	0.6302	1.0323	0.0107	0.0037	0.0379	0.0181	−0.0085	0.0048	0.8161
	Liquidity	(12.33)	(11.19)	(6.49)	(9.24)	(6.11)	(2.61)	(4.17)	(11.20)	(−4.86)	(1.55)	
Broad	P&S TB	0.0262	0.1624	0.5953	0.4090	0.0048	0.0130	0.0153	0.0302	−0.0079	0.0031	0.8164
Market	Liquidity	(9.73)	(14.10)	(5.50)	(2.20)	(1.75)	(3.36)	(1.74)	(18.74)	(−4.43)	(1.23)	
Return	P&S Stock	0.0258	0.3365	0.0918	0.4937	0.0258	0.0026	0.0282	0.0258	−0.0077	0.0017	0.8149
	Liquidity	(9.44)	(18.63)	(1.04)	(3.23)	(9.37)	(2.17)	(3.12)	(15.33)	(−4.33)	(0.57)	
	Broad Market	0.0231	0.3465	0.1146	0.3283	0.0231	0.0028	0.0331	0.0240	−0.0067	0.0003	0.8133
	Liquidity	(8.46)	(19.49)	(1.19)	(2.00)	(8.02)	(2.77)	(3.67)	(14.06)	(−3.80)	(0.10)	

coefficient on maturity is positive, indicating that bonds with higher maturity have higher required rate of returns. The coefficients on MKT, SMB, and HML betas are significant only in the Litzenberger–Ramaswamy regression. The coefficient on the dummy variable RUN is negative as expected but is significant only in the Litzenberger–Ramaswamy regression. The coefficient on the Flag dummy variable is significantly positive, giving some evidence that the required rate of return tends to rise after Treasuries go off the run. The R^2 values are high (0.82), indicating that the model has done a good job in capturing cross-sectional variation in bond returns.

B.2. Results Based on Alternative Measures of Liquidity and Market Returns

In the base model, the market return beta is estimated using the stock market return, while the liquidity beta is estimated using the Treasure market liquidity series. Since both stocks and bonds are involved in the cross-sectional regressions, we also calculate market returns and marketwide liquidity using information from both markets. In this section, we present results based on alternative measures of market-wide liquidity and market returns.

We first obtain liquidity beta using (i) the Pastor–Stambaugh equity liquidity factor for the stock market, kindly provided by Lubos Pastor, and (ii) the broad market liquidity factor, which is a simple average of the liquidity factors for equity and Treasury markets. The liquidity beta estimated using the Pastor–Stambaugh equity liquidity series measures sensitivities of Treasury bond returns to the equity market liquidity condition. The liquidity beta estimated using the broad market liquidity series measures sensitivities of Treasury bond returns to the liquidity conditions in both Treasury and equity markets.

The cross-sectional regression results using the equity and broad market liquidity betas are reported in the second and third rows in Panels A and B of Table VII, respectively. Here the market return beta is still estimated using stock market returns. Again, we report the results for both the Fama–MacBeth and Litzenberger–Ramaswamy regressions. When the liquidity beta is estimated from the Pastor–Stambaugh equity liquidity factor, we find that the coefficient on β_L is barely significant at the 5% level, while the coefficient on PIN remains significant at the 1% level in the Fama–MacBeth regression. The results show a positive relation between expected Treasury returns and systematic equity liquidity risk. Thus, there appears to be a cross-market liquidity risk effect. When the liquidity beta measure is based on the broad market liquidity factor, the coefficient on β_L becomes more significant. This is more likely because the broad market liquidity factor contains the Treasury market liquidity information, which tends to have a closer relation with Treasury returns. Overall, the goodness of fit is slightly higher for the regression with the Treasury market liquidity factor. The t-value is also highest for the liquidity beta associated with the Treasury market liquidity factor, suggesting that cross-sectional returns are more closely related to the own market systematic liquidity risk. Similar results are found for the Litzenberger–Ramaswamy regressions, which tend to produce higher t-values.

Furthermore, to assess the sensitivity of regression results to the market return beta measure, we construct a broad market return based on the value-weighted average of equity, corporate bond, and Treasury market returns. The results of the cross-sectional regressions based on the broad market return beta are reported in rows 4 to 6 in Panels A and B of Table VII. The results show that the market return beta becomes more significant in the Fama–MacBeth regressions. The higher t-value suggests that the broad market return beta captures the systematic market risk of Treasury securities better than the stock market return beta. This is likely because the broad market returns contain the Treasury market return, which is more closely related with individual Treasury security returns. Using the broad market return to estimate the market return beta has little impact on the significance of PIN. The liquidity betas also remain significant. A similar pattern is found for the Litzenberger–Ramaswamy regressions. Thus, the choice of market return proxies does not appear to have a material effect on the statistical significance of liquidity and information risks in the cross-sectional tests of expected Treasury returns.

C. Robustness to Traditional Liquidity and Information Risk Measures

In this section, we examine the robustness of our results to several widely used microstructure-based liquidity and information measures. The results above show that β_L and PIN explain cross-sectional variations of Treasury bond returns very well. However, a potential concern is that β_L and PIN have high explanatory power because they proxy for the effects of the traditional liquidity and information variables. To address this issue, we examine how our liquidity and information risk variables fare against these traditional variables in the cross-sectional regression. The first alternative variable we consider is bid-ask spread. Amihud and Mendelson (1986) find a positive relationship between bid-ask spreads and expected stock returns. On the other hand, EHOH (2002) document mixed results using more recent data. Given the higher transaction costs associated with higher spreads, it is not surprising that higher spreads could lead to higher returns. A more important question is whether bid-ask spreads contain the effects of liquidity and information risk variables. The second variable we consider is volatility. High PINs are usually associated with high order imbalances, which may cause high volatility in bond returns and spreads. Also, high volatility is thought to thwart market liquidity. So liquidity and information risk variables may proxy for return and spread volatilities. The third variable is volume. Many studies have found that volume explains asset price behavior. In empirical exercises, volume is often used as a measure of the information content of financial transactions. Theory suggests that informed traders should be more active when the trading volume is high or the market is deep (see Admati and Pfleiderer (1988)). Since PIN reflects informed traders' activity, it could be a proxy for the effect of volume. High volume also improves market liquidity. Volume is a widely cited measure of market liquidity because more active markets tend to be more liquid. The fourth variable is order imbalance, which may be linked to information asymmetry and inventory problems. Brandt and Kavajecz (2004) show that order imbalance affects daily variation in bond yields. Since PIN is computed from daily buy and sell orders, it may contain similar information as order imbalance. Furthermore, a higher order imbalance results in a larger price impact and lower liquidity. Last, if not least, depth is commonly thought to be a good measure of market liquidity. A natural question is whether our liquidity beta may simply be a proxy for market depth.

We incorporate the above microstructure variables into the cross-sectional regression. The average daily percentage bid-ask spread in the preceding year is used as the spread variable. The average daily standard deviations of bond returns (STD) and spreads (STDS) in the preceding year are used as the volatility proxies. Abnormal volume is defined as the percentage of deviation of the volume in the preceding year from the average volume for the entire sample period for each maturity portfolio. This abnormal volume is assigned to each bond in the portfolio. Previous equity market studies have used the proportion of volume to shares outstanding as the proxy for volume effect. GovPX does not provide information for the number of units outstanding for each Treasury security. Nevertheless, the abnormal volume measure proposed here should capture a similar volume effect. Order imbalance is the difference between buy and sell dollar volume divided by total purchase and sell dollar volume. We employ the market quality index (average quoted depth/percentage bid-ask spread) suggested by Bollen and Whaley (1998) to measure market depth. Beber et al. (2007) show that this variable is more parsimonious. We calculate the average daily order imbalance and MQI in the preceding year and use them as alternative information and liquidity measures.

Table VIII reports the results of incorporating all of the alternative explanatory variables. The first row in each panel reports the results using the Treasury market liquidity series to estimate market beta risk. We find that β_L and PIN remain quite significant even when all the alternative variables are included in the cross-sectional regression. In the Fama–MacBeth regressions, the coefficient on MQI is significant, indicating that it has incremental explanatory power. Order imbalance is significant when stock and broad market liquidity measures are used. Similar results obtain for the Litzenberger–Ramaswamy regressions though with greater estimation efficiency. Overall, the R^2 value increases by about 4% when all alternative variables are added. We find that the coefficients on β_L and PIN remain highly significant even after including all bond characteristic and trading variables in the cross-sectional regressions. The results show that the positive relationship between expected bond returns and liquidity and information risks is quite robust to inclusion of traditional macrostructure-based proxy variables. Thus, our liquidity and information risk measures are not serving as a proxy for the joint effects of these alternative variables. Instead, there is strong evidence that the systematic liquidity risk of Pastor and Stambaugh (2003) and PIN of EHOH (2002) are important determinants of required Treasury returns.[24]

[24] We also conduct a test on the potential error-in-variable (EIV) problem for PIN using a portfolio approach similar to Fama and French (1992) and Easley, Hvidkjaer, and O'Hara (2002). We find that this is not a concern and our results remain unchanged after correcting the potential EIV problem. The results for this robustness check are available from the authors.

Table VIII
Alternative Regressions

This table reports time-series averages of the coefficients in cross-sectional asset pricing tests. *Spread* is the average daily percentage spread for each bond in preceding year, *n*-1. *STD* (*STDS*) is the standard deviation of daily returns (spreads) in year *n*-1. *Ab_Vol* is the abnormal volume in year *n*-1. The abnormal volume is the difference between the volume in year *n*-1 and the average volume over the entire sample period divided by the sample average volume for each bond. *IMB* is average daily order imbalance in year *n*-1, where order imbalance is the difference between purchase and sell orders divided by the sum of purchase and sell orders. *MQI* is average depth divided by percentage quoted spread averaged daily in year *n*-1.The remaining variables are as defined in Table VII and *t*-values are given in parentheses.

		Intercept	β_{MKT}	β_{SMB}	β_{HML}	β_{TERM}	β_L	*PIN*	*TM*	*RUN*	*Flag*	*Spread*	*STDS*	*STD*	*Ab_Vol*	*IMB*	*MQI*	R^2
Panel A. Fama–MacBeth Regressions																		
Stock	P&S TB	0.0136	1.2121	0.7131	0.5541	0.0408	0.0858	0.0338	0.0236	−0.0165	0.0043	0.3650	0.2857	0.3467	−0.0277	0.0142	−0.0765	0.8629
Market	Liquidity	(0.68)	(1.48)	(0.51)	(0.71)	(2.11)	(2.68)	(2.96)	(1.66)	(−1.65)	(0.89)	(0.55)	(1.07)	(2.89)	(−1.71)	(1.65)	(−4.70)	
Return	P&S Stock	0.0218	1.2135	0.7963	0.7029	0.0137	0.0277	0.0331	0.0243	−0.0101	0.0046	0.5120	0.4095	0.3824	−0.0196	0.0270	−0.0777	0.8615
	Liquidity	(1.22)	(1.52)	(0.69)	(0.79)	(0.97)	(2.79)	(1.90)	(1.56)	(−1.14)	(0.89)	(0.76)	(1.68)	(2.76)	(−1.44)	(2.77)	(−3.91)	
	Broad Mkt	0.0375	1.3357	0.8849	0.9609	0.0072	0.0439	0.0391	0.0280	−0.0188	0.0089	0.4593	0.3006	0.3054	−0.0187	0.0264	−0.0753	0.8624
	Liquidity	(2.07)	(0.65)	(0.46)	(0.57)	(0.44)	(3.15)	(2.16)	(1.83)	(−1.63)	(1.94)	(0.61)	(1.01)	(2.29)	(−1.39)	(2.40)	(−4.07)	
Broad	P&S TB	0.0229	0.1809	0.5158	0.7009	0.0218	0.0638	0.0372	0.0219	−0.0076	0.0164	0.4944	0.3268	0.3707	−0.0293	0.0181	−0.0794	0.8606
Market	Liquidity	(1.48)	(2.37)	(0.28)	(0.66)	(0.96)	(3.15)	(1.76)	(1.81)	(−0.93)	(2.99)	(0.68)	(1.11)	(3.03)	(−1.43)	(1.82)	(−2.08)	
Return	P&S Stock	0.0239	0.2195	0.4357	0.5002	0.0142	0.0131	0.0477	0.0303	−0.0083	0.0071	0.4918	0.3672	0.3883	−0.0391	0.0170	−0.0863	0.8588
	Liquidity	(1.52)	(3.21)	(0.32)	(0.58)	(0.76)	(2.59)	(2.29)	(2.46)	(−1.01)	(1.57)	(0.69)	(1.51)	(3.09)	(−1.89)	(1.73)	(−3.76)	
	Broad Mkt	0.0149	0.2098	0.4154	0.7027	0.0125	0.0146	0.0446	0.0361	−0.0123	0.0035	0.4643	0.2070	0.3659	−0.0375	0.0178	−0.0827	0.8596
	Liquidity	(0.89)	(2.71)	(0.29)	(0.78)	(0.54)	(2.05)	(2.12)	(2.59)	(−1.23)	(0.69)	(0.56)	(0.72)	(2.83)	(−1.84)	(1.52)	(−1.95)	
Panel B. Litzenberger–Ramaswamy WLS Regressions																		
Stock	P&S TB	0.0131	1.2100	0.5998	0.7150	0.0207	0.0723	0.0367	0.0216	−0.0151	0.0039	0.4758	0.1763	0.3577	−0.0269	0.0249	−0.0681	0.8629
Market	Liquidity	(4.07)	(12.66)	(4.53)	(6.19)	(6.76)	(11.24)	(4.65)	(11.88)	(−8.05)	(1.33)	(2.70)	(1.76)	(11.92)	(−7.26)	(4.22)	(−8.51)	
Return	P&S Stock	0.0276	0.9547	0.6180	0.5579	0.0214	0.0162	0.0311	0.0205	−0.0168	0.0060	0.7033	0.2063	0.4483	−0.0237	0.0205	−0.0601	0.8615
	Liquidity	(8.42)	(13.21)	(6.93)	(5.35)	(9.94)	(14.57)	(3.89)	(12.50)	(−9.36)	(1.91)	(3.99)	(2.08)	(14.90)	(−6.54)	(3.47)	(−8.89)	
	Broad Mkt	0.0292	0.9175	0.5562	0.4910	0.0170	0.0197	0.0326	0.0200	−0.0133	0.0050	0.2232	0.2069	0.3799	−0.0245	0.0282	−0.0659	0.8624
	Liquidity	(8.91)	(11.60)	(7.87)	(5.32)	(8.35)	(10.30)	(4.18)	(12.00)	(−7.13)	(1.59)	(1.24)	(2.08)	(12.42)	(−6.77)	(4.73)	(−10.01)	
Broad	P&S TB	0.0262	0.3409	0.5645	0.4211	0.0123	0.0280	0.0275	0.0234	−0.0142	0.0063	0.7159	0.2357	0.4753	−0.0243	0.0283	−0.0533	0.8606
Market	Liquidity	(2.44)	(33.07)	(6.38)	(2.44)	(4.18)	(6.17)	(3.44)	(14.25)	(−7.98)	(2.16)	(4.14)	(2.38)	(15.57)	(−6.57)	(4.83)	(−7.57)	
Return	P&S Stock	0.0176	0.4063	0.5066	0.6417	0.0154	0.0093	0.0254	0.0231	−0.0144	0.0033	0.7172	0.2164	0.5809	−0.0244	0.0174	−0.0666	0.8588
	Liquidity	(3.17)	(34.27)	(6.52)	(4.29)	(5.15)	(3.87)	(3.12)	(13.52)	(−7.77)	(1.08)	(3.77)	(2.19)	(18.96)	(−6.66)	(2.83)	(−7.89)	
	Broad Mkt	0.0184	0.3979	0.5035	0.6509	0.0157	0.0182	0.0383	0.0219	−0.0143	0.0033	0.8395	0.2039	0.3036	−0.0254	0.0295	−0.0640	0.8596
	Liquidity	(4.42)	(32.13)	(6.74)	(3.88)	(5.13)	(5.04)	(4.68)	(12.64)	(−7.60)	(1.06)	(4.52)	(2.05)	(9.96)	(−6.88)	(4.84)	(−8.31)	

In sum, our empirical analysis shows that the positive relation between expected bond returns and β_L/PIN is very robust. Even after we control for the effects of four systematic risk factors (β_{MKT}, β_{SMB}, β_{HML}, β_{TERM}), bond characteristics (TM, RUN, Flag), and a wide variety of traditional liquidity and information measures (Spread, STD, STDS, Ab_Vol, IMB, and MQI), the positive relations remain quite strong. Our results strongly suggest that liquidity and information risks are important determinants of expected Treasury returns.

IV. Conclusion

In this paper, we provide a comprehensive study of the effects of liquidity and information risks on the expected returns of U.S. Treasury bonds. We show that the marketwide liquidity and PIN estimated from bond data capture the liquidity condition and informed trading in the Treasury market very well. More important, we document a strong positive and economically significant relation between expected Treasury bond returns and our measures of liquidity and information risks, controlling for the effects of other systematic risks, and bond characteristics. This relation is very robust to different empirical specifications and a wide variety of microstructure-based proxies of liquidity and informed trading used in the existing literature. Our results demonstrate the generality of the Pastor–Stambaugh liquidity risk and the PIN measure for explaining asset returns in different financial markets. Our findings suggest that term structure modeling should consider liquidity and information risk effects in order to help improve our understanding of yield curve dynamics.

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