Liquidity of Corporate Bonds

Jack Bao, Jun Pan and Jiang Wang*

May 19, 2009

Abstract

This paper examines the liquidity of corporate bonds and its asset-pricing implications using an empirical measure of illiquidity based on the magnitude of transitory price movements. Relying on transaction-level data for a broad cross-section of corporate bonds from 2003 through 2008, we find the illiquidity in corporate bonds to be significant, substantially greater than what can be explained by bid-ask bounce, and closely linked to liquidity-related bond characteristics. More importantly, we find a strong commonality in the time variation of bond illiquidity, which rises sharply during market crises and reaches a high in 2008 during the credit market turmoil. Monthly changes in this aggregate bond illiquidity are strongly related to changes in the CBOE VIX Index. Examining its relation with bond pricing, we find that our measure of illiquidity explains the cross-sectional variation in bond yield spreads with large economic significance, indicating the importance of liquidity in bond valuation.

*Bao is from MIT Sloan School of Management (jackbao@mit.edu); Pan is from MIT Sloan School of Management and NBER (junpan@mit.edu); and Wang is from MIT Sloan School of Management, CCFR and NBER (wangj@mit.edu). The authors thank Andrew Lo, Ananth Madhavan, Ken Singleton and participants at the 2008 JOIM Spring Conference, 2008 Conference on Liquidity at University of Chicago, 2008 Q Group Fall Conference, and seminar participants at Columbia, Kellogg, Rice, Stanford, University of Rhode Island, University of Wisconsin at Madison for helpful comments. Support from the outreach program of J.P. Morgan is gratefully acknowledged.

1 Introduction

The liquidity of the corporate bond market has been of interest for researchers, practitioners and policy makers. Many studies have attributed deviations in corporate bond prices from their "theoretical values" to the influence of illiquidity in the market.[1] Yet, our understanding of how to quantify illiquidity remains limited. Without a credible measure of illiquidity, it is difficult to have a direct and serious examination of the asset-pricing influence of illiquidity and its implications on market efficiency.

Several measures of illiquidity have been considered for corporate bonds. A simple measure is the effective bid-ask spread, which is analyzed in detail by Edwards, Harris, and Piwowar (2007).[2] Although the bid-ask spread is a direct and potentially important indicator of illiquidity, it does not fully capture many important aspects of liquidity such as market depth and resilience. Alternatively, relying on theoretical pricing models to gauge the impact of illiquidity allows for direct estimation of its influence on prices, but suffers from potential mis-specifications of the pricing model.

In this paper, we rely on a salient feature of illiquidity to measure its significance. It has been well recognized that the lack of liquidity in an asset gives rise to transitory components in its prices.[3] The magnitude of such transitory price movements reflects the degree of illiquidity in the market. Since transitory price movements lead to negatively serially correlated price changes, the negative of the autocovariance in price changes, which we denote by γ, provides a simple, yet robust measure of illiquidity. In the simplest case when the transitory price movements arise purely from bid-ask bounce, as considered by Roll (1984), $2\sqrt{\gamma}$ equals the bid-ask spread. But in more general cases, γ captures the broader impact of illiquidity on prices, above and beyond the effect of bid-ask spread. Moreover, it does so without relying on specific bond pricing models.

Indeed, our results show that the lack of liquidity in the corporate bond market is substantial, significantly more severe than what can be explained by bid-ask bounce. More

[1]For example, Huang and Huang (2003) find that yield spreads for corporate bonds are too high to be explained by credit risk and question the economic content of the unexplained portion of yield spreads (see also Colin-Dufresne, Goldstein, and Martin (2001) and Longstaff, Mithal, and Neis (2005)). Bao and Pan (2008) document a significant amount of transitory excess volatility in corporate bond returns and attribute this excess volatility to the illiquidity of corporate bonds.

[2]See also Bessembinder, Maxwell, and Venkataraman (2006) and Goldstein, Hotchkiss, and Sirri (2007).

[3]Niederhoffer and Osborne (1966) are among the first to recognize the relation between negative serial covariation and illiquidity. More recent theoretical work in establishing this link include Grossman and Miller (1988), Huang and Wang (2007), and Vayanos and Wang (2009), among others.

importantly, taking advantage of this measure of illiquidity, we are able to analyze the time variation of the aggregate illiquidity in corporate bonds and its asset-pricing implications. The main results of our paper can be further detailed as follows.

First, we uncover a level of illiquidity in corporate bonds that is important both economically and statistically. Using TRACE, a transaction-level dataset, we estimate γ for a broad cross-section of the most liquid corporate bonds in the U.S. market. Our results show that, using trade-by-trade data, the median estimate of γ is 0.41, and the mean estimate is 0.60; using daily data, the median γ is 0.67, and the mean γ is 1.04. Both means are highly statistically significant. To judge the economic significance of such magnitudes, we can use the quoted bid-ask spreads to calculate a bid-ask implied γ. For the same sample of bonds and for the same sample period, we find that the median and mean γ implied by the quoted bid-ask spreads are respectively 0.031 and 0.045, which are tiny fractions of our estimated γ. An alternative comparison is to use Roll's model to calculate the γ-implied bid-ask spread, which is $2\sqrt{\gamma}$, and compare it with the quoted bid-ask spread.[4] Using our median estimates of γ, the γ-implied bid-ask spread is \$1.28 using trade-by-trade data and \$1.64 using daily data, significantly larger than the median quoted bid-ask spread of \$0.31 or the estimated bid-ask spread reported by Edwards, Harris, and Piwowar (2007) (see Section 5 for more details). Such comparisons suggest that our illiquidity measure γ captures the price impact of illiquidity above and beyond the effect of simple bid-ask bounce.

Second, we establish a robust connection between our illiquidity measure γ and bond characteristics known to be relevant for liquidity. Regressing our illiquidity measure γ on a spectrum of bond characteristics, we find a strong positive relation between γ and bond age — a variable widely used in the fixed-income market as a proxy of illiquidity; and a strong negative relation between γ and the size of bond issuance — another variable potentially linked to bond liquidity. Moreover, we find that the measure of illiquidity captured by γ is related to but goes beyond the information contained in the quoted bid-ask spreads. Specifically, adding the bid-ask implied γ as an additional explanatory variable, we find that it has a positive cross-sectional relation with our γ measure, but it does not alter the established cross-sectional relation between γ and bond characteristics, including age and issuance size. Controlling for bond characteristics including age and issuance size, we also find that bonds

[4] Roll's model assumes that directions of trades are serially independent. For a given bid-ask spread, positive serial correlation in trade directions, which could be the case when liquidity is lacking and traders break up their trades, tends to increase the implied bid-ask spreads for a given γ. This could potentially increase the magnitude of the γ implied bid-ask spreads, further deepening its difference from the quoted bid-ask spreads.

with smaller average trade sizes typically have higher illiquidity measure γ.

Third, focusing on the systematic component of bond illiquidity, we construct a monthly time-series of aggregate γ.[5] Examining its variation over time and its connection with broader financial markets, we find interesting patterns in the aggregate γ. Before the onset of the sub-prime crisis in 2007, there is a general trend of decreasing γ, indicating an overall improvement of liquidity in the corporate bond market during this period. Against this backdrop of an overall time trend, however, we find substantial monthly movements in the aggregate measure of illiquidity. In particular, the aggregate γ rises sharply during market crises, including the periods that lead to the downgrade of Ford and GM bonds to junk status, the sub-prime mortgage crisis that started in August 2007, and the credit market turmoil following the collapse of Lehman Brothers. For example, before August 2007, our aggregate γ hovered around a level near 0.37 with a monthly standard deviation of 0.08. In August 2007, it jumped by over 60% to a level near 0.70. During the year after that, stabilized around 0.81 with a monthly standard deviation of 0.12. Then it shot to 1.59 in September 2008 and a high of 2.85 in October 2008.

More interestingly, this common illiquidity component is closely connected with the changing conditions of broader financial markets. Regressing monthly changes in aggregate γ on changes in CBOE VIX, we find a positive and strongly significant relation with an R-squared of 64%. We also, consider other variables such as the volatility of aggregate bond returns, CDS spread, term spread, default spread and lagged returns on the aggregate stock and bond markets, finding some relation to our aggregate illiquidity measure. But the most robust relation by far lies with VIX. Moreover, this connection with VIX is not simply a 2008 phenomena. For the subperiod that excludes 2008, monthly changes in our aggregate γ remain closely related to monthly changes in VIX.

The fact that the VIX index, measured from index options, is the main variable in explaining changes in aggregate illiquidity of corporate bonds is rather intriguing. Indeed, from an aggregate perspective, this implies that the sources of our estimated bond market illiquidity are not contained just in the bond market. This raises the possibility of illiquidity being an additional source of systemic risk, as examined by Chordia, Roll, and Subrahmanyam (2000) and Pastor and Stambaugh (2003) for the equity market.

[5] Starting with the bond-level γ, we can construct our aggregate illiquidity measure using either the cross-sectional mean or median. Both measures generate similar results. The mean measure, however, does exhibit more dramatic time variation, especially during crises. To be more conservative, we use the cross-sectional median as our aggregate γ measure.

Fourth, we examine the asset-pricing implications of bond illiquidity. We find that our illiquidity measure γ explains the cross-sectional variation of average bond yield spreads with large economic significance. Controlling for bond rating categories, we perform monthly cross-sectional regressions of bond yield spreads on bond γ. We find a coefficient of 0.21. Given that the cross-sectional standard deviation of γ is 1.79, our result implies that for two bonds in the same rating category, a two standard deviation difference in their γ leads to a difference in their yield spreads as large as 75 bps. This is comparable to the difference in yield spreads between Baa and Aaa/Aa bonds, which is 113 bps in our sample. In contrast, quoted bid-ask spreads have rather limited, if any, economic significance in explaining the cross-sectional average yield spreads. Moreover, the economic significance of our illiquidity measure remains robust in its magnitude and statistical significance after we control for a spectrum of variables related to the bond's fundamental information as well as bond characteristics. In particular, liquidity related variables such as bond age, issuance size, quoted bid-ask spread, and average trade size do not change this result in a significant way.

In addition to the main results summarized above, we provide detailed analyses of our illiquidity measure to further shed light on the nature of illiquidity in corporate bonds. We explore the dynamic properties of illiquidity by estimating the magnitude of price reversals after skipping one or several trades. We find significant price reversals even after skipping a trade, indicating a mean-reversion in price changes that lasts for more than one trade.[6] We also find that negative price changes, likely caused by excess selling pressure, are followed by stronger reversals than positive price changes, resulting in an asymmetry in γ.[7] We find that price changes associated with large trades exhibit weaker reversals than those associated with small trades, and this effect is robust after controlling for the overall bond liquidity. Although this result suggests a strong link between liquidity and trade sizes, it does not imply more liquidity for larger trades since both trade sizes and prices are endogenous.

Our paper is related to the growing literature on the impact of liquidity on corporate bond yields. Using illiquidity proxies that include quoted bid-ask spreads and the percentage of zero returns, Chen, Lesmond, and Wei (2007) find that more illiquid bonds earn higher yield spreads. Using nine liquidity proxies including issuance size, age, missing prices, and yield volatility, Houweling, Mentink, and Vorst (2003) reach similar conclusions for euro corporate

[6] This is consistent with the fact that our γ measured at the daily level, capturing this persistent transaction-level mean-reversion cumulatively, yields a higher magnitude than its counterpart at the transaction level.

[7] Such an asymmetry was described as a characteristic of the impact of illiquidity on prices by Huang and Wang (2007). Our results provide an interesting empirical test of this proposition.

bonds. de Jong and Driessen (2005) find that systematic liquidity risk factors for the Treasury bond and equity markets are priced in corporate bonds, and Downing, Underwood, and Xing (2005) address a similar question. Using a proprietary dataset on institutional holdings of corporate bonds, Nashikkar, Mahanti, Subrahmanyam, Chacko, and Mallik (2008) and Mahanti, Nashikkar, and Subrahmanyam (2008) propose a measure of latent liquidity and examine its connection with the pricing of corporate bonds and credit default swaps. We contribute to this growing body of literature by proposing a measure of illiquidity that is theoretically motivated and empirically more direct and demonstrating its economic economic importance both in terms the risk and valuation of corporate bonds.

It should be noted that the estimation of our illiquidity measures relies on transactions prices. For relatively liquid bonds, transactions are fairly frequent and our estimates are more reliable. This constrains our analysis to more liquid bonds. Since the goal of this paper is to demonstrate the potential importance of illiquidity for corporate bonds, doing so for the more liquid bonds actually strengthens our case. However, a large fraction of corporate bonds are not traded often. For those bonds, one may follow the methods of Edwards, Harris, and Piwowar (2007), which rely on more detailed trade information in addition to prices.

The paper is organized as follows. Section 2 describes the data used in our analysis and provides summary statistics. The main results of our paper are reported in Section 3, and Section 4 provides further analyses of our illiquidity measure. Section 5 compares our illiquidity measure with the effect of bid-ask spreads. Section 6 concludes.

2 Data Description and Summary

The main dataset used for this paper is FINRA's TRACE (Transaction Reporting and Compliance Engine). This dataset is a result of recent regulatory initiatives to increase the price transparency in secondary corporate bond markets. FINRA, formerly the NASD, is responsible for operating the reporting and dissemination facility for over-the-counter corporate bond trades. On July 1, 2002, the NASD began Phase I of bond transaction reporting, requiring that transaction information be disseminated for investment grade securities with an initial issue size of \$1 billion or greater. Phase II, implemented on April 14, 2003, expanded reporting requirements, bringing the number of bonds to approximately 4,650. Phase III, implemented completely on February 7, 2005, required reporting on approximately 99% of all public transactions. Trade reports are time-stamped and include information on the clean price and par value traded, although the par value traded is truncated at \$1 million for speculative grade bonds and at \$5 million for investment grade bonds.

In our study, we drop the early sample period with only Phase I coverage. We also drop all of the Phase III only bonds. We sacrifice in these two dimensions in order to maintain a balanced sample of Phase I and II bonds from April 14, 2003 to December 31, 2008. Of course, new issuances and retired bonds generate some time variation in the cross-section of bonds in our sample. After cleaning up the data, we also take out the repeated inter-dealer trades by deleting trades with the same bond, date, time, price, and volume as the previous trade.[8] We further require the bonds in our sample to have frequent enough trading so that the illiquidity measure can be constructed from the trading data. Specifically, during its existence in the TRACE data, a bond must trade on at least 75% of its relevant business days in order to be included in our sample. Finally, to avoid bonds that show up just for several months and then disappear from TRACE, we require the bonds in our sample to be in existence in the TRACE data for at least one full year.

Table 1 summarizes our sample, which consists of frequently traded Phase I and II bonds from April 2003 to December 2008. There are 1,205 bonds in our full sample, although the total number of bonds does vary from year to year. The increase in the number of bonds from 2003 to 2004 could be a result of how NASD starts its coverage of Phase III bonds, while the gradual reduction of number of bonds from 2004 through 2008 is a result of matured or retired bonds.

The bonds in our sample are typically large, with a median issuance size of \$717 million, and the representative bonds in our sample are investment grade, with a median rating of 6, which translates to Moody's A2. The average maturity is close to 6 years and the average age is about 4 years. Over time, we see a gradual reduction in maturity and increase in age. This can be attributed to our sample selection which excludes bonds issued after February 7, 2005, the beginning of Phase III.[9]

Given our selection criteria, the bonds in our sample are more frequently traded than a typical bond. The average monthly turnover — the bond's monthly trading volume as a percentage of its issuance size — is 7.51%, the average number of trades in a month is 181. The median trade size is \$338,000. For the the whole sample in TRACE, the average monthly

[8]This includes cleaning up withdrawn or corrected trades, dropping trades with special sale conditions or special prices, and correcting for obviously mis-reported prices.

[9]We will discuss later the effect, if any, of this sample selection on our results. An alternative treatment is to include in our sample those newly issued bonds that meet the Phase II criteria, but this is difficult to implement since the Phase II criteria are not precisely specified by NASD.

Table 1: **Summary Statistics**

Panel A: Bonds in Our Sample

	2003			2004			2005			2006			2007			2008		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std	mean	med	std	mean	med	std
#Bonds	773			1,150			1,093			970			831			670		
Issuance	1,012	1,000	730	864	700	683	861	700	689	844	681	666	842	650	676	847	688	678
Rating	5.59	5.67	2.55	6.77	6.00	3.84	7.05	6.00	4.07	7.41	6.00	4.52	7.51	6.00	4.73	7.98	7.00	4.71
Maturity	7.33	5.23	6.80	7.88	5.66	7.24	7.36	5.19	7.24	7.02	4.66	7.24	6.92	4.42	7.31	6.70	3.96	7.35
Coupon	5.87	6.00	1.66	5.87	6.13	1.87	5.83	6.00	1.87	5.78	5.88	1.90	5.81	6.00	1.90	5.90	6.00	1.86
Age	2.68	1.94	2.62	3.17	2.38	2.94	3.90	3.17	2.94	4.74	3.96	2.95	5.69	4.73	3.07	6.66	5.74	3.15
Turnover	11.57	8.31	9.52	9.40	7.10	7.51	8.26	6.17	6.90	6.30	5.11	4.78	5.08	4.10	3.90	4.82	4.11	3.33
Trd Size	584	462	488	527	401	477	430	336	385	383	293	344	336	256	313	257	183	247
#Trades	243	148	360	180	122	191	201	121	291	158	109	144	143	102	127	200	126	219
Avg Ret	0.59	0.38	0.85	0.64	0.35	1.57	-0.03	0.17	1.04	0.63	0.39	1.10	0.39	0.45	0.71	-1.18	0.27	3.59
Volatility	2.49	2.25	1.48	1.76	1.61	1.09	2.17	1.44	2.87	1.79	1.22	2.06	1.86	1.33	1.82	6.99	4.03	8.68
Price	108	109	10	106	106	11	103	103	11	100	101	11	102	101	12	96	100	20

Panel B: All Bonds Reported in TRACE

	2003			2004			2005			2006			2007			2008		
	mean	med	std	mean	med	std	mean	med	std	mean	med	std	mean	med	std	mean	med	std
#Bonds	4,161			15,270			23,415			22,627			23,640			23,442		
Issuance	470	260	542	220	85	384	189	50	363	209	56	371	221	42	403	219	30	417
Rating	5.30	5.00	2.60	6.46	6.00	3.26	7.37	7.00	4.00	7.18	6.00	4.26	6.77	6.00	4.19	6.75	6.00	4.29
Maturity	8.51	4.55	10.77	8.34	5.38	8.88	7.86	5.05	8.41	8.01	5.12	8.66	8.08	5.05	8.97	8.00	4.94	8.97
Coupon	6.51	6.75	1.69	5.76	5.85	1.96	5.80	5.70	2.16	5.74	5.63	2.13	5.60	5.55	2.16	5.35	5.50	2.32
Age	4.61	3.75	3.87	3.24	1.82	3.61	3.37	2.00	3.73	3.64	2.44	3.78	3.77	2.83	3.71	4.06	3.33	3.70
Turnover	5.87	3.82	6.36	5.20	2.58	7.07	3.95	2.44	4.52	3.56	2.18	4.18	3.29	1.97	4.02	3.10	1.84	3.69
Trd Size	1,017	532	1,263	534	59	991	477	55	869	509	58	905	487	49	899	386	46	761
#Trades	66	19	184	31	9	86	26	6	90	21	5	56	21	5	71	28	5	97
Avg Ret	0.63	0.38	4.07	0.50	0.28	2.56	0.11	0.21	2.27	0.85	0.54	2.06	0.36	0.45	2.02	-0.90	0.14	6.33
Volatility	2.73	2.37	2.27	1.93	1.68	1.29	2.65	1.94	2.81	2.31	1.75	2.28	2.42	1.96	2.24	9.34	5.79	11.08
Price	109	110	12	104	103	16	100	100	17	99	99	19	100	100	34	92	97	22

#Bonds is the number of bonds. *Issuance* is the bond's amount outstanding in millions of dollars. *Rating* is a numerical translation of Moody's rating: 1=Aaa and 21=C. *Maturity* is the bond's time to maturity in years. *Coupon*, reported only for fixed coupon bonds, is the bond's coupon payment in percentage. *Age* is the time since issuance in years. *Turnover* is the bond's monthly trading volume as a percentage of its issuance. *Trd Size* is the average trade size of the bond in thousands of dollars of face value. *#Trades* is the bond's total number of trades in a month. Med and std are the time-series averages of the cross-sectional medians and standard deviations. For each bond, we also calculate the time-series mean and standard deviation of its monthly log returns, whose cross-sectional mean, median and standard deviation are reported under *Avg Ret* and *Volatility*. *Price* is the average market value of the bond in dollars.

turnover is 4.07%, the average number of trades in a month is 26 and the median trade size is \$61,000.[10] Thus, the bonds in our sample are also relatively more liquid. Given that our focus is to study the significance of illiquidity for corporate bonds, such a bias in our sample towards more liquid bonds, although not ideal, will only help to strengthen our results if they show up for the most liquid bonds.

In addition to the TRACE data, we use CRSP to obtain stock returns for the market and the respective bond issuers. We use FISD to obtain bond-level information such as issue date, issuance size, coupon rate, and credit rating, as well as to identify callable, convertible and putable bonds. We use Bloomberg to collect the quoted bid-ask spreads for the bonds in our sample, from which we have data for 1,170 out of the 1,205 bonds in our sample.[11] We use Datastream to collect Lehman Bond indices to calculate the default spread and returns on the aggregate corporate bond market and also to gather CDS spreads. To calculate yield spreads for individual corporate bonds, we obtain Treasury bond yields from the Federal Reserve, which publishes constant maturity Treasury rates for a range of maturities. Finally, we obtain the VIX index from CBOE.

3 Main Results

3.1 Measure of Illiquidity

Although a precise definition of illiquidity and its quantification will depend on a specific model, two properties are clear. First, illiquidity arises from market frictions, such as costs and constraints for trading and capital flows; second, its impact to the market is transitory. Our empirical measure of illiquidity is motivated by these two properties.

As such, the focus, as well as the contribution, of our paper is mainly empirical. To facilitate our analysis, however, let us think in terms of the following simple model. Let P_t denote the clean price — the full value minus accrued interest since the last coupon date — of a bond at time t. We start by assuming that P_t consists of two components:

$$P_t = F_t + u_t \,. \tag{1}$$

The first component F_t is its fundamental value — the price in the absence of frictions, which follows a random walk; the second component u_t comes from the impact of illiquidity, which

[10] A more complete summary of the whole TRACE sample is provided in an online appendix to this paper.

[11] We follow Chen, Lesmond, and Wei (2007) in using the Bloomberg Generic (BGN) bid-ask spread. This spread is calculated using a proprietary formula which uses quotes provided to Bloomberg by a proprietary list of contributors. These quotes are indicative rather than binding.

is transitory (and uncorrelated with the fundamental value).[12] In such a framework, the magnitude of the transitory price component u_t characterizes the level of illiquidity in the market. Our measure of illiquidity is aimed at extracting the transitory component in the observed price P_t. Specifically, let $\Delta P_t = P_t - P_{t-1}$ be the price change from $t-1$ to t. We define the measure of illiquidity γ by

$$\gamma = -\text{Cov}\left(\Delta P_t, \Delta P_{t+1}\right). \tag{2}$$

With the assumption that the fundamental component F_t follows a random walk, γ depends only on the transitory component u_t, and it increases with the magnitude of u_t.

Several comments are in order before we proceed with our empirical analysis of γ. First, we know little about the dynamics of u_t, other than its transitory nature. For example, when u_t follows an AR(1) process, we have $\gamma = (1-\rho)\sigma^2/(1+\rho)$, where σ is the instantaneous volatility of u_t, and $0 \leq \rho < 1$ is its persistence coefficient. In this case, while γ does provide a simple gauge of the magnitude of u_t, it combines various aspects of u_t (e.g., σ and ρ). Second, for the purpose of measuring illiquidity, other aspects of u_t that are not fully captured by γ may also matter. In other words, γ itself gives only a partial measure of illiquidity. Third, given the potential richness in the dynamics of u_t, γ will in general depend on the horizon over which we measure price changes. This horizon effect is important because γ measured over different horizons may capture different aspects of u_t or illiquidity. For most of our analysis, we will use either trade-by-trade prices or end of the day prices in estimating γ. Consequently, our γ estimate captures more of the high frequency components in transitory price movements.

Table 2 summarizes the illiquidity measure γ for the bonds in our sample. Focusing first on Panel A, in which γ is estimated bond-by-bond using either trade-by-trade or daily data, we see an illiquidity measure of γ that is important both economically and statistically.[13] For the full sample period from 2003 through 2008, our illiquidity measure γ has a cross-sectional average of 0.60 with a robust t-stat of 22.43 when estimated using trade-by-trade data, and

[12] Such a separation assumes that the fundamental value F_t carries no time-varying risk premium. This is a reasonable assumption over short horizons. It is equivalent to assuming that high frequency variations in expected returns are ultimately related to market frictions — otherwise, arbitrage forces would have driven them away. To the extent that illiquidity can be viewed as a manifestation of these frictions, price movements giving rise to high frequency variations in expected returns should be included in u_t. Admittedly, a more precise separation of F_t and u_t must rely on a pricing theory incorporating frictions or illiquidity. See, for example, Huang and Wang (2007) and Vayanos and Wang (2009).

[13] To be included in our sample, the bond must trade on at least 75% of business days and at least 10 observations of the paired price changes, $(\Delta P_t, \Delta P_{t-1})$, are required to calculate γ. In calculating γ using daily data, price changes may be between prices over multiple days if a bond does not trade during a day. We limit the difference in days to one week though this criteria rarely binds due to our sample selection criteria.

Table 2: **Measure of Illiquidity** $\gamma = -\text{Cov}\left(P_t - P_{t-1}, P_{t+1} - P_t\right)$

Panel A: Individual Bonds							
	2003	2004	2005	2006	2007	2008	Full
Trade-by-Trade Data							
Mean γ	0.67	0.68	0.57	0.48	0.52	0.89	0.60
Median γ	0.46	0.40	0.32	0.27	0.31	0.63	0.41
Per t $\geq$ 1.96	99.35	97.56	99.63	99.59	99.52	98.06	99.83
Robust t-stat	16.79	16.10	18.61	19.97	19.20	16.21	22.43
Daily Data							
Mean γ	1.05	1.00	0.90	0.77	0.97	2.39	1.04
Median γ	0.71	0.55	0.46	0.42	0.59	1.50	0.67
Per t $\geq$ 1.96	94.55	90.43	96.15	96.27	94.90	93.70	98.76
Robust t-stat	22.29	17.49	26.38	25.10	23.01	16.04	28.35

Panel B: Bond Portfolios							
	2003	2004	2005	2006	2007	2008	Full
Equal-weighted	-0.0021	-0.0044	-0.0024	0.0009	-0.0004	-0.0393	-0.0087
t-stat	-0.38	-1.17	-0.86	0.75	-0.21	-1.08	-1.29
Issuance-weighted	0.0019	-0.0040	-0.0011	0.0008	0.0006	-0.0402	-0.0077
t-stat	0.28	-0.98	-0.35	0.48	0.19	-1.04	-1.09

Panel C: Implied by Quoted Bid-Ask Spreads							
	2003	2004	2005	2006	2007	2008	Full
Mean implied γ	0.045	0.040	0.050	0.050	0.051	0.056	0.045
Median implied γ	0.037	0.030	0.027	0.024	0.027	0.050	0.031

At the individual bond level, γ is calculated using either trade-by-trade or daily data. Per t-stat $\geq$ 1.96 reports the percentage of bond with statistically significant γ. Robust t-stat is a test on the cross-sectional mean of γ with standard errors corrected for cross-sectional and time-series correlations. At the portfolio level, γ is calculated using daily data and the Newey-West t-stats are reported. Monthly quoted bid-ask spreads, which we have data for 1,170 out of 1,205 bonds in our sample, are used to calculate the implied γ.

an average of 1.04 with a robust t-stat of 28.35 using daily data.[14] More importantly, the significant mean estimate of γ is not generated by just a few highly illiquid bonds. Using trade-by-trade data, the cross-sectional median of γ is 0.41, and 99.83% of the bonds have a statistically significant γ (t-stat of γ greater than or equal to 1.96); using daily data, the cross-sectional median of γ is 0.67 and over 98% of the bonds have a statistically significant γ. Moreover, breaking our full sample by year shows that the illiquidity measure γ is important and stable across years.[15]

For each bond, we can further break down its overall illiquidity measure γ to gauge the relative contribution from trades of various sizes. Specifically, for each bond, we sort its trades by size into the smallest 30%, middle 40%, and largest 30% and then estimate γ^{small}, γ^{medium} and γ^{large} using prices associated with the corresponding trade sizes. The results are summarized in Table 14 in the Appendix. We find that our overall illiquidity measure is not driven only by small trades. In particular, we find significant illiquidity across all trade sizes. For example, using daily data, the cross-sectional means of γ^{small}, γ^{medium} and γ^{large} are 1.44, 0.91, and 0.47, respectively, each with very high statistical significance.

As a comparison to the level of illiquidity for individual bonds, Panel B of Table 2 reports γ measured using equal- or issuance-weighted portfolios constructed from the same cross-section of bonds and for the same sample period. In contrast to its counterpart at the individual bond level, γ at the portfolio level is slightly negative, rather small in magnitude, and statistically insignificant. This implies that the transitory component extracted by our γ measure is idiosyncratic in nature and gets diversified away at the portfolio level. It does not imply, however, that the illiquidity in corporate bonds lacks a systematic component, which we will examine later in Section 3.3.

Panel C of Table 2 provides another and perhaps more important gauge of the magnitude of our estimated γ for individual bonds. Using quoted bid-ask spreads for the same cross-section of bonds and for the same sample period, we estimate a bid-ask implied γ for each

[14] The robust t-stats are calculated using standard errors that are corrected for cross-sectional and time-series correlations. Specifically, the moment condition for estimating γ is $\hat{\gamma} + \Delta P_t^i \Delta P_{t-1}^i = 0$ for all bond i and time t, where ΔP is demeaned. We can then correct for cross-sectional and time-series correlations in $\Delta P_t^i \Delta P_{t-1}^i$ using standard errors clustered by bond and day.

[15] Our γ measure could be affected by the presence of persistent small trades, which could be a result of the way dealers deal bonds to retail traders. We thank the referee for raising this point. Such persistent small trades will bias our illiquidity measure downward. In other words, our γ measures would have been larger in the absence of such persistent small trades. Moreover, it will have a larger impact on γ measured using prices associated small trade sizes. As we discuss in the next paragraph, we find significant illiquidity across all trade sizes.

bond by computing the magnitude of negative autocovariance that would have been generated by bid-ask bounce. For the full sample period, the cross-sectional mean of the implied γ is 0.045 and the median is 0.031, which are more than one order of magnitude smaller than the empirically observed γ for individual bonds. As shown later in the paper, not only does the quoted bid-ask spread fail to capture the overall level of illiquidity, but it also fails to explain the cross-sectional variation in bond illiquidity and its asset pricing implications.

Although our focus is on extracting the transitory component at the trade-by-trade and daily frequencies, it is nevertheless interesting to provide a general picture of γ over varying horizons. Moving from the trade-by-trade to daily horizon, our results in Table 2 show that the magnitude of the illiquidity measure γ becomes larger. Given that the autocovariance at the daily level cumulatively captures the mean-reversion at the trade-by-trade level, this implies that the mean-reversion at the trade-by-trade level persists for a few trades before fully dissipating, which we show in Section 4.1. Moving from the daily to weekly horizon, we find that the magnitude of γ increases from an average level of 1.04 to 1.11, although its statistical significance decreases to a robust t-stat of 11.70, and 74.94% of the bonds in our sample have a positive and statistically significant γ at this horizon. Extending to the bi-weekly and monthly horizons, γ starts to decline in both magnitude and statistical significance.[16]

As mentioned earlier in the section, the transitory component u_t might have richer dynamics than what can be offered by a simple AR(1) structure for u_t. By extending γ over various horizons, we are able to uncover some of the dynamics. We show in Section 4.1 that at the trade-by-trade level u_t is by no means a simple AR(1). Likewise, in addition to the mean-reversion at the daily horizon that is captured in this paper, the transitory component u_t may also have a slow moving mean-reversion component at a longer horizon. To examine this issue more thoroughly is an interesting topic, but requires time-series data for a longer sample period than ours.[17]

[16]In addition to reducing the available data, the higher differencing intervals also decreases the signal to noise ratio as the fundamental volatility starts to build up. See Harris (1990) for the exact small sample moments of the serial covariance estimator and of the standard variance estimator for price changes generated by the Roll spread model.

[17]By using monthly bid prices from 1978 to 1998, Khang and King (2004) report contrarian patterns in corporate bond returns over horizons of one to six months. Instead of examining autocovariance in bond returns, their focus is on the cross-sectional effect. Sorting bonds by their past monthly (or bi-monthly up to 6 months) returns, they find that past winners under perform past losers in the next month (or 2-month up to 6 months). Their result, however, is relatively weak and is significant only in the early half of their sample and goes away in the second half of their sample (1988–1998).

3.2 Illiquidity and Bond Characteristics

Our sample includes a broad cross-section of bonds, which allows us to examine the connection between our illiquidity measure γ and various bond characteristics, some of which are known to be linked to bond liquidity. The variation in our illiquidity measure γ and bond characteristics are reported in Table 3. We use daily data to construct yearly estimates for γ for each bond and perform pooled regressions on various bond characteristics. Reported in square brackets are the t-stat's calculated using standard errors clustered by year.[18]

We find that older bonds on average have higher γ, and the results are robust regardless of which control variables are used in the regression. On average, a bond that is one-year older is associated with an increase of 0.1 in its γ, which accounts for 10% of the full-sample average of γ. Given that the age of a bond has been widely used in the fixed-income market as a proxy for illiquidity, it is important that we establish this connection between our illiquidity measure γ and age. Similarly, we find that bonds with smaller issuance tend to have larger γ. We also find that bonds with longer time to maturity and lower credit ratings typically have higher γ.

Using weekly bond returns, we also estimate, for each bond, its betas on the aggregate stock- and bond-market returns, using the CRSP value-weighted index as a proxy for the stock market and the Lehman US Bond Index as a proxy for the bond market. We find that γ is positively related to the stock beta and weakly related to bond beta. However, in unreported results, we find that the inclusion of the idiosyncratic volatility (estimated from the residual of the betas regression) drives out the significance of both stock and bond betas.

Given that we have transaction-level data, we can also examine the connection between our illiquidity measure and bond trading activity. We find that, by far, the most interesting variable is the average trade size of a bond. In particular, bonds with smaller trade sizes have higher illiquidity measure γ.

To examine the cross-sectional connection between our illiquidity measure and the quoted bid-ask spreads, we use the quoted bid-ask spreads for each bond in our sample to calculate the negative of the bid-ask spread implied autocovariance, or bid-ask implied γ. We find a positive relation between our γ measure and the γ measure implied by the quoted bid-ask spread.[19] The regression coefficient is on average around 4 and is statistically significant.

[18]Running Fama-MacBeth regressions generates very similar results.

[19]As it is possible that the relation between γ and γ implied by quoted bid-ask spreads is mechanical due to spreads being a fixed proportion of prices and price levels being different, we also examine the relation between

Table 3: **Variation in γ and Bond Characteristics**

Cons	1.36	1.59	2.53	1.15	1.35	1.59	1.49
	[4.55]	[4.71]	[5.23]	[2.91]	[6.80]	[7.97]	[3.12]
Age	0.10	0.08	0.05	0.09	0.09	0.09	0.09
	[3.49]	[3.61]	[2.31]	[3.07]	[2.91]	[2.82]	[3.75]
Maturity	0.07	0.08	0.08	0.08	0.07	0.08	0.08
	[11.51]	[9.02]	[10.28]	[9.52]	[9.95]	[8.58]	[8.25]
ln(Issuance)	-0.26	-0.27	-0.06	-0.30	-0.24	-0.28	-0.25
	[-4.20]	[-5.75]	[-3.95]	[-10.05]	[-5.55]	[-6.18]	[-3.78]
Rating	0.04	0.06	0.07	0.05	0.03	0.06	0.01
	[4.10]	[5.41]	[6.13]	[6.24]	[2.99]	[7.53]	[1.59]
beta (stock)	0.58						
	[4.84]						
beta (bond)	0.18						
	[1.75]						
Turnover		-0.01					
		[-1.04]					
ln(Trd Size)			-0.41				
			[-4.72]				
ln(Num Trades)				0.11			
				[1.45]			
Quoted BA γ					3.90		
					[4.75]		
CDS Dummy						-0.07	
						[-0.94]	
CDS Spread							0.06
							[5.86]
Obs	4,781	5,323	5,323	5,323	5,076	4,565	3,317
R-sqd (%)	27.49	25.86	29.17	25.85	26.05	24.71	23.33

Panel regression with γ as the dependent variable. T-stats are reported in square brackets using standard errors clustered by year. *Issuance* is the bond's amount outstanding in millions of dollars. *Rating* is a numerical translation of Moody's rating: 1=Aaa and 21=C. *Age* is the time since issuance in years. *Maturity* is the bond's time to maturity in years. *Turnover* is the bond's monthly trading volume as a percentage of its issuance. *Trd Size* is the average trade size of the bond in thousands of dollars of face value. *#Trades* is the bond's total number of trades in a month. *beta(stock) and beta(bond)* are obtained by regressing weekly bond returns on weekly returns on the CRSP value-weighted index and the Lehman US bond index. *Quoted BA* γ is the γ implied by the quoted bid-ask spreads. *CDS Dummy* is 1 if the bond has credit default swaps traded on its issuer. *CDS Spread* is the spread on the five-year CDS of the bond issuer in %. Data is from 2003 to 2008 except for regressions with CDS information which start in 2004.

The magnitude of the coefficient implies that a one unit difference in γ implied by quoted bid-ask spreads gets amplified to four times the difference in our measure of γ. Adding the bid-ask implied γ as an explanatory variable, however, does not alter the relation between our γ measure and liquidity-related bond characteristics such as age and size. Overall, we find that the magnitude of illiquidity captured by our γ measure is related to but goes beyond the information contained in the quoted bid-ask spreads.

Finally, given the extent of CDS activity during our sample period and its close relation with the corporate bond market, it is also interesting for us to explore the connection between γ and information from the CDS market. We first use a CDS dummy, which is one if the bond issuer has credit default swaps traded on it and zero otherwise. About 71% of the bond-years in our sample have traded CDS. Using data from 2004 through 2007, we find that, after controlling for bond age, maturity, issuance size and rating, bonds with CDS traded have γ's that are on average 0.13 lower than bonds without CDS traded, and this difference has a robust t-stat of 3.79. But as shown in Table 3, the difference becomes smaller in magnitude and is statistically insignificant after including 2008. In other words, pre-2008, whether or not a bond has CDS traded on its issuer contains information about its liquidity. But in 2008, this label of CDS trading becomes unimportant.

Relating our γ measure to the CDS spread of its issuer also introduces some interesting results. Using data from 2004 through 2007, we find that, after controlling for bond age, maturity, issuance size, and rating, higher CDS spreads are correlated with higher γ, although the connection is only borderline significant with a t-stat of 1.74. With the inclusion of 2008, however, the connection becomes much stronger in magnitude and statistical significance (the t-stat is now 5.86). But this is mainly a result that both γ and CDS spreads increased dramatically in 2008. Repeating the same analysis in a Fama-MacBeth regression, we find that the cross-sectional connection between γ and CDS spread is statistically insignificant even with the inclusion of 2008. This is consistent with the fact that γ and CDS spreads potentially carry rather different economic content: while γ is a measure of bond-level illiquidity, the CDS spread captures more of the fundamental default risk and/or risk premiums.

γ calculated using log price changes and γ implied by bid-ask spreads, finding a significant correlation between the two variables.

3.3 Commonality in Illiquidity and Market Conditions

We next examine the time variation of illiquidity in the bond market. From Table 2, we see a steady reduction in the annual γ averaged over all bonds in our sample from 2003 through 2006. For example, the median γ using daily data is 0.71 in 2003, which decreases monotonically to 0.42 in 2006, suggesting an overall improvement of liquidity in the bond market from 2003 through 2006. During 2007, however, the median γ jumped back to 0.59 and in 2008, the median γ dramatically increased to 1.50, reflecting worsening liquidity in the market.[20] Using the cross-sectional mean of γ, we can observe the same and even a somewhat more dramatic pattern.

We now investigate this time variation more closely. For this, we turn our attention to monthly fluctuations in the illiquidity measure γ. Monthly illiquidity measures γ are calculated for each bond using daily data within that month.[21] We then use the cross-sectional median γ as our aggregate γ measure. Compared with the cross-sectional mean of γ, the median γ is a more conservative measure and is less sensitive to those highly illiquid bonds that were most severely affected by the credit market turmoil.

In Figure 3.3, we plot our aggregate γ along with the CBOE VIX index. The top panel plots the entire time series from 2003 through 2008, while the bottom panel focuses on the period before the default of Lehman Brothers in September 2008. From both panels, it is clear that the aggregate γ exhibits significant time variation, which suggests that there are important commonalities in the illiquidity measure captured by our bond-level γ. In particular, after decreasing markedly but relatively smoothly during 2003 and the first half of 2004, it reversed its trend and started to climb up in late 2004 and then spiked in April/May 2005. This rise in γ coincides with the downgrade of Ford and GM to junk status in early May 2005, which

[20]By focusing only on Phase I and II bonds in TRACE to maintain a reasonably balanced sample, we did not include bonds that were included only after Phase III, which was fully implemented on February 7, 2005. Consequently, new bonds issued after that date were excluded from our sample, even though some of them would have been eligible for Phase II had they been issued earlier. As a result, starting from February 7, 2005, we have a population of slowly aging bonds. Since γ is positively related to age, the overall downward trend in γ would have been more pronounced had we been able to maintain a more balanced sample. It should be mentioned that the sudden increases in aggregate γ during crises are too large to be explained by the slow aging process. Finally, to avoid regressing trend on trend, the time-series regression results presented later in this section are based on regressing changes on changes.

[21]In calculating the monthly autocovariance of price changes, we can demean the price change using the sample mean within the month, within the year, or over the entire sample period. It depends on whether we view the monthly variation in the mean of price change as noise or as some low-frequency movement related to the fundamental. In practice, however, this time variation is rather small compared with the high-frequency bouncing around the mean. As a result, demeaning using the monthly mean or the sample mean generates very similar results. Here we report the results using the former.

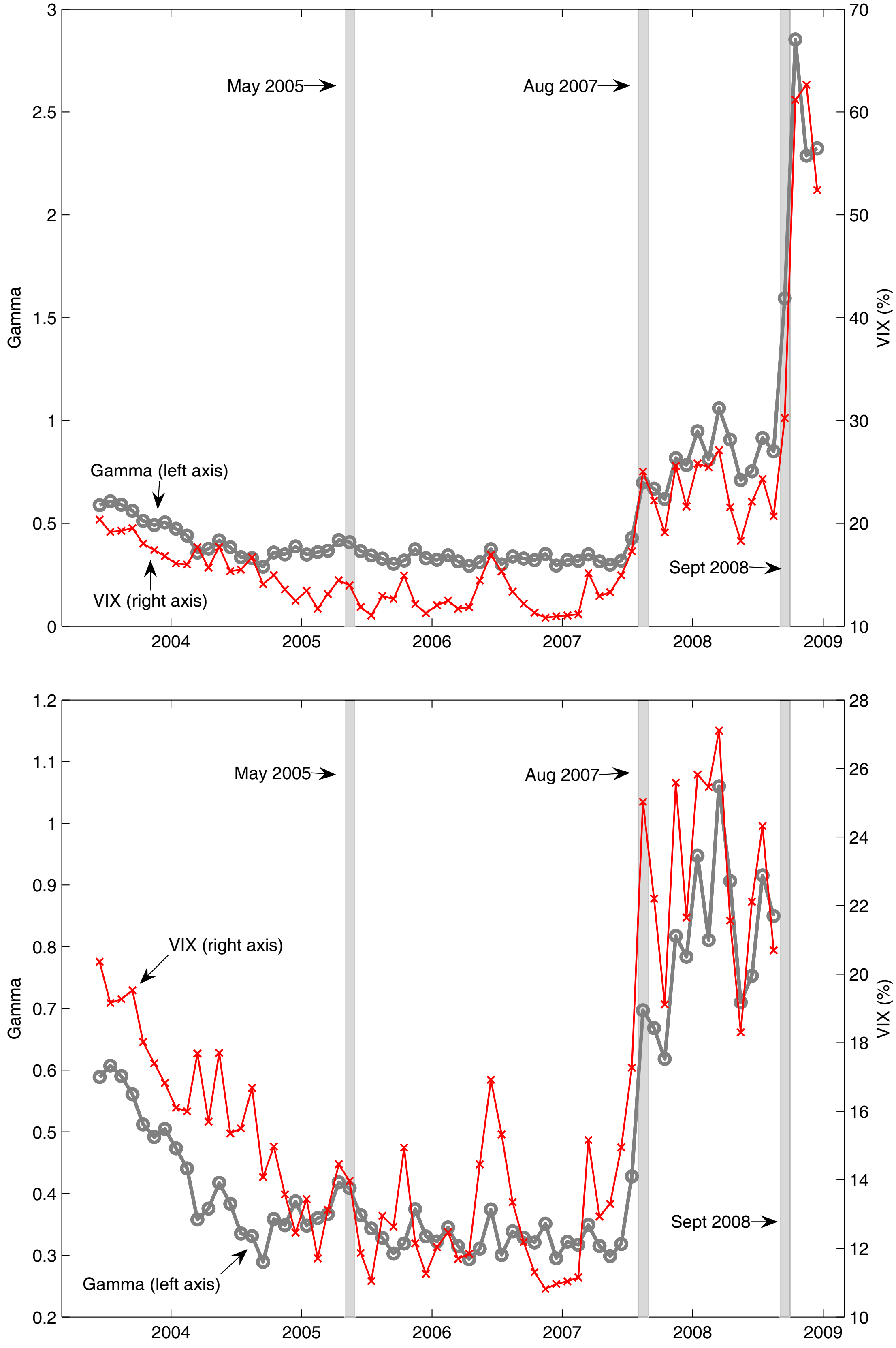

Figure 1: Monthly time-series of aggregate γ and CBOE VIX. The bottom is for the subperiod before the collapse of Lehman.

rattled the credit market. The illiquidity measure γ quieted down somewhat through 2006, but rose sharply in August 2007, when the sub-prime mortgage crisis first hit. Its August 2007 value of 0.70 is quite dramatic compared to its late 2006 value of 0.30. Though this rise is fairly sharp compared to changes in γ preceding 2007, it is small compared to changes in 2008. Aggregate γ remained in the 0.8 to 1.1 range for much of 2008 before jumping to 1.59 in September 2008, when Lehman Brothers filed for bankruptcy. In October 2008, γ rose further to 2.85 before slightly declining towards the end of 2008.

The fact that γ increased drastically during periods of credit market turmoil in our sample indicates that not only does bond market illiquidity vary over time, but, more importantly, it varies together with the changing conditions of the market. In Figure 3.3, along with the aggregate γ, we also plot the CBOE VIX index, which is also known as the "fear gauge" of the market. From the top panel, we see a rather close and almost one-for-one comovement between the two time series after the onset of the subprime crisis starting in August 2007. The bottom panel of Figure 3.3 shows that this close relation is present even before γ and VIX spiked when Lehman defaulted in September 2008. Indeed, as reported in Table 4, regressing changes in γ on contemporaneous changes in VIX, we obtain a slope coefficient of 0.0351 with a t-stat of 8.15 and the adjusted R-squared of the OLS regression is 64%. Excluding data from 2008, the positive relation is still robust: the slope coefficient is 0.0187 with a t-stat of 3.46 and the R-squared is 40%.

In addition to VIX, we also plot in Figure 3.3 the aggregate γ along with several other variables linked to general market conditions. To capture the conditions of the credit market, we use default spread, measured as the difference in yields between AAA- and BBB-rated corporate bonds, using the Lehman US Corporate Intermediate Indices. To capture the overall volatility of the corporate bond market, we construct monthly estimates of annualized bond return volatility using daily returns to the Lehman US Investment Grade Corporate Index. From the figure, we see some connection between these variables and our aggregate γ measure, especially during the more recent crisis. Compared with the close comovement between VIX and aggregate γ observed in Figure 3.3, however, the connection seems weaker.

To quantify the link with the market-wide variables, we further report in Table 4 the univariate regression results. We find that changes in γ and contemporaneous changes in bond return volatility are related with a coefficient of 0.0409 and a t-stat of 2.03. But this result is mostly driven by 2008 and it disappears when the data from 2008 is excluded. We find no statistically significant relation between changes in γ and changes in default spread. As

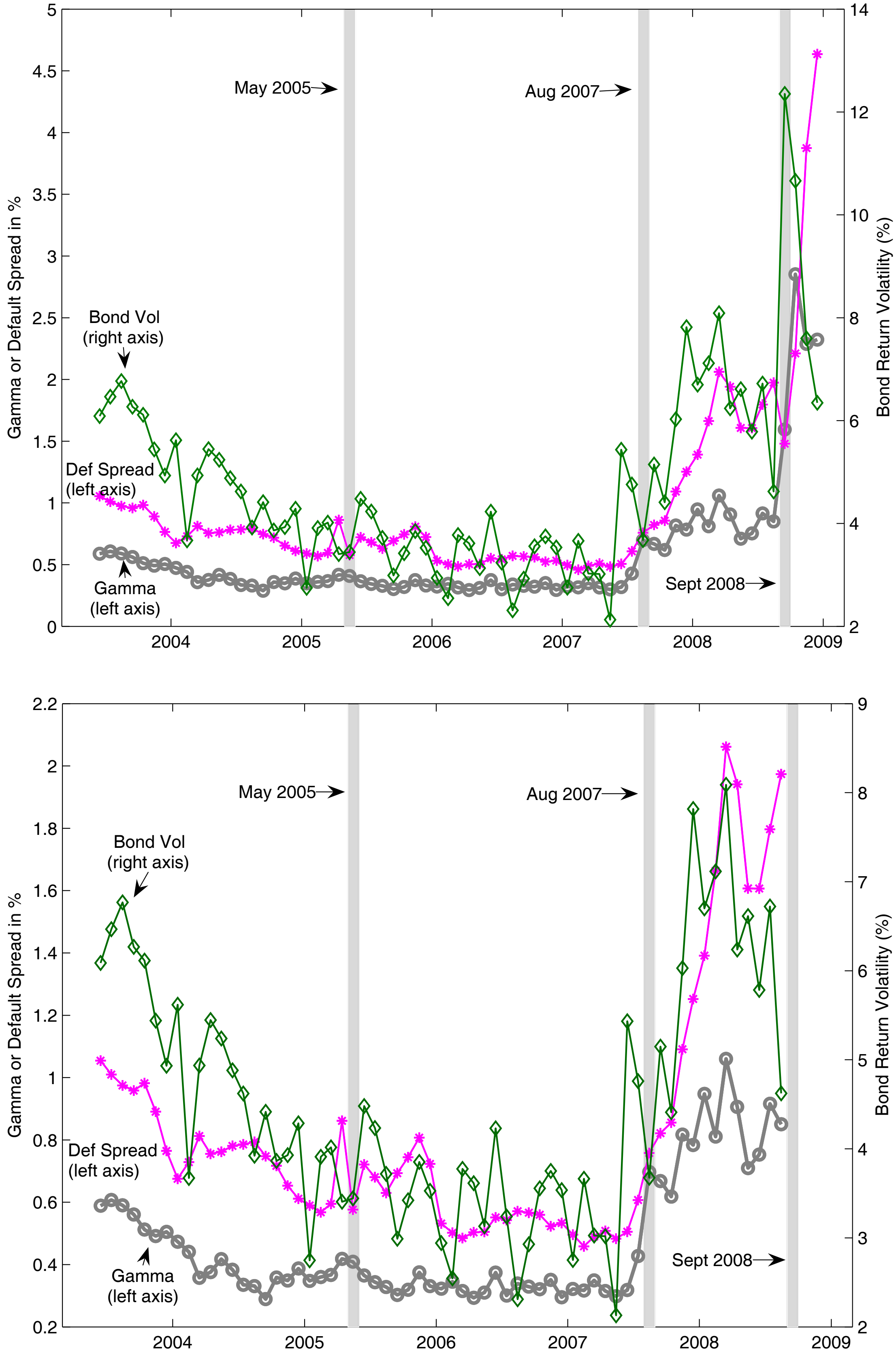

Figure 2: Monthly time-series of aggregate γ, corporate bond return volatility, and default spread. The bottom panel is for the subperiod before the collapse of Lehman.

Table 4: **Time Variation in Aggregate γ and Market Variables**

Panel A: Full Sample Period 2003-2008								
Cons	0.0224	0.0068	0.0042	0.0261	0.0251	0.0241	0.0205	0.0088
	[1.00]	[0.86]	[0.46]	[1.06]	[0.96]	[1.15]	[1.15]	[1.11]
Δ VIX	0.0351							0.0339
	[8.15]							[5.70]
Δ Bond Volatility		0.0409						0.0375
		[2.03]						[3.26]
Δ CDS Index			0.2288					0.0098
			[1.94]					[0.15]
Δ Term Spread				0.3496				
				[1.45]				
Δ Default Spread					-0.0283			
					[-0.24]			
Lagged Stock Return						-0.0061		
						[-0.81]		
Lagged Bond Return							-0.0303	
							[-1.62]	
Adj R-sqd (%)	64.12	6.50	14.68	10.32	-1.40	-0.10	6.08	69.96
Panel B: Sub-Sample Period 2003-2007								
Cons	0.0012	0.0004	0.0014	0.0033	0.0003	0.0094	0.0021	0.0069
	[0.13]	[0.05]	[0.26]	[0.35]	[0.04]	[0.92]	[0.24]	[1.08]
Δ VIX	0.0187							0.0156
	[3.46]							[3.29]
Δ Bond Volatility		-0.0054						
		[-0.64]						
Δ CDS Index			0.3500					0.0809
			[2.67]					[0.89]
Δ Term Spread				0.0868				
				[1.85]				
Δ Default Spread					0.2705			
					[1.72]			
Lagged Stock Return						-0.0088		-0.0047
						[-2.27]		[-1.63]
Lagged Bond Return							-0.0127	-0.0058
							[-3.65]	[-1.10]
Adj R-sqd (%)	40.29	-1.22	32.25	3.20	13.25	11.36	6.17	50.58

Monthly changes in γ regressed on monthly changes in bond index volatility, VIX, CDS index, term spread, default spread, and lagged stock and bond returns. The Newey-West t-stats are reported in square brackets. Regressions with CDS Index do not include 2003 data.

another proxy for the overall default risk, we also consider an average CDS index, constructed as the average of five-year CDS spreads covered by CMA Datavision in Datastream. We find a positive and significant relation between changes in aggregate γ and changes in CDS index. Interestingly, the connection is in fact stronger pre-2008.

Table 4 also reports the relation between monthly changes of our aggregate γ and the performance of the aggregate stock and bond markets in the previous month. We find that our aggregate γ has statistically insignificant relations with lagged aggregate bond and stock market returns. In the pre-2008 period, however, aggregate γ typically increased following down markets. Towards the end of 2008, our aggregate illiquidity measure flattened out while stock and bond markets continued to decline.

The various market condition variables considered so far are closely inter-connected. To evaluate their relative importance, Table 4 also reports the result of the multivariate regression using all variables that are univariately significant in full or sub-sample regressions. VIX remains robustly significant and bond volatility remains significant only when 2008 is included while the CDS index does not. Our illiquidity measure is in fact most related to variables that tend to measure aggregate uncertainty and fear.

Our time-series analysis of the aggregate illiquidity reveals two important properties of γ as a measure of illiquidity for corporate bonds. First, there exists commonality in the illiquidity of individual bonds, which is reflected in the significant time variation in aggregate γ. Second, such common movements in bond market illiquidity are closely connected with overall market conditions in an important way.

3.4 Bond Yield Spreads and Illiquidity

We now examine the pricing implications of bond illiquidity. For this purpose, we focus on the bond yield spread, which is the difference between the corporate bond yield and the Treasury bond yield of the same maturity. For Treasury yields, we use the constant maturity rate published by the Federal Reserve and use linear interpolation whenever necessary. We perform monthly cross-sectional regressions of the yield spreads on the illiquidity measure γ, along with a set of control variables. We report our results for our full sample of bonds, including both investment-grade and junk bonds.[22]

[22]For robustness, we also repeat our analysis for only investment-grade bonds, and the results are available in the online appendix of this paper. Given that the Phase I and II bonds in TRACE are predominantly investment grade, this sub-sample analysis is important for us to rule out the possibility that our result is driven just by a handful of unrepresentative junk bonds.

The results are reported in Table 5, where the t-stat's are calculated using the Fama-MacBeth standard errors with serial correlation corrected using Newey and West (1987). To include callable bonds in our analysis, which constitute a large portion of our sample, we use a callable dummy, which is one if a bond is callable and zero otherwise.[23] We exclude all convertible and putable bonds from our analysis. In addition, we also include three rating dummies for A, Baa, and junk ratings, respectively. The first column in Table 5 shows that the average yield spread of the Aaa and Aa bonds in our sample is 113 bps, relative to which the A bonds are 69 bps higher, Baa bonds are 119 bps higher, and junk bonds are 541 bps higher.

As reported in the second column of Table 5, adding γ to the regression does not bring much change to the relative yield spreads across ratings. This is to be expected since γ should capture more of a liquidity effect, and less of a fundamental risk effect, which is reflected in the differences in ratings. More importantly, we find that the coefficient on γ is 0.21 with a t-stat of 7.08. This implies that for two bonds in the same rating category, if one bond, presumably less liquid, has a γ that is higher than the other by 1, the yield spread of this bond is on average 21 bps higher than the other. To put an increase of 1 in γ in context, the cross-sectional standard deviation of γ is on average 1.79 in our sample. From this perspective, our illiquidity measure γ is economically important in explaining the cross-sectional variation in average bond yields.

To control for the fundamental risk of a bond above and beyond what is captured by the rating dummies, we use equity volatility estimated using daily equity returns of the bond issuer. Effectively, this variable is a combination of the issuer's asset volatility and leverage. We find this variable to be important in explaining yield spreads. As shown in the third column of Table 5, the slope coefficient on equity volatility is 0.06 with a t-stat of 3.82. That is, a ten percentage point increase in the equity volatility of a bond issuer is associated with a 60 bps increase in the bond yield. While adding γ improves the cross-sectional R-squared from a time-series average of 42.79% to 46.55%, adding equity volatility improves the R-squared to 53.07%. Such R-squared's, however, should be interpreted with caution since it is a time-series average of cross-sectional R-squared, and does not take into account the cross-sectional correlations in the regression residuals. By contrast, our reported Fama-MacBeth t-stat's do and γ has a stronger statistical significance. It is also interesting to observe that by adding equity volatility, the magnitudes of the rating dummies decrease significantly. This is to be

[23]In the Appendix, we also report results with callable bonds excluded.

Table 5: **Bond Yield Spread and Illiquidity Measure γ**

Cons	1.13	0.96	-0.70	-0.70	0.06	-0.36	-0.64	0.02	-1.31	1.66	-0.26	0.20
	[3.46]	[3.31]	[-1.55]	[-1.58]	[0.35]	[-1.20]	[-1.91]	[0.08]	[-2.55]	[2.11]	[-1.17]	[1.76]
γ		0.21		0.21	0.14	0.14	0.15	0.13	0.13		0.21	0.13
		[7.08]		[7.01]	[8.23]	[4.51]	[4.72]	[4.27]	[4.59]		[6.38]	[9.32]
Equity Vol			0.06	0.06	0.02	0.06	0.05	0.06	0.05		0.06	0.02
			[3.82]	[3.40]	[2.99]	[3.41]	[3.36]	[3.43]	[3.32]		[3.55]	[2.96]
CDS Spread					0.53							0.52
					[12.20]							[11.90]
Age						0.06	0.07	0.05	0.07			
						[2.60]	[3.05]	[2.47]	[2.76]			
Maturity						0.00	0.00	0.00	0.00			
						[0.14]	[0.04]	[0.10]	[0.21]			
ln(Issuance)						-0.10	-0.08	-0.05	-0.19			
						[-2.26]	[-1.97]	[-1.49]	[-3.37]			
Turnover							0.03					
							[5.89]					
ln(Trd Size)								-0.13				
								[-2.56]				
ln(#Trades)									0.31			
									[5.00]			
Quoted B/A Spread										-1.34	-0.98	-0.28
										[-1.09]	[-1.12]	[-0.63]
Call Dummy	-0.44	-0.47	0.12	0.07	0.04	0.07	0.09	0.08	0.12	-0.38	0.18	0.08
	[-1.05]	[-1.10]	[2.14]	[1.52]	[1.01]	[1.61]	[2.13]	[1.56]	[2.19]	[-1.11]	[1.48]	[1.04]
A Dummy	0.69	0.66	0.19	0.16	0.21	0.16	0.15	0.18	0.23	0.67	0.09	0.16
	[1.52]	[1.52]	[1.14]	[1.10]	[1.46]	[1.05]	[0.97]	[1.18]	[1.39]	[1.56]	[0.96]	[1.64]
BAA Dummy	1.19	1.08	0.74	0.67	0.50	0.64	0.59	0.71	0.76	1.18	0.63	0.49
	[2.85]	[2.91]	[2.77]	[2.68]	[2.51]	[2.42]	[2.12]	[2.57]	[2.49]	[3.15]	[3.42]	[2.79]
Junk Dummy	5.41	5.00	3.86	3.57	1.28	3.53	3.48	3.59	3.62	5.43	3.58	1.36
	[4.38]	[4.12]	[3.96]	[3.65]	[4.20]	[3.76]	[3.70]	[3.73]	[3.72]	[3.97]	[3.53]	[3.57]
Obs	679	670	679	670	502	670	670	670	670	633	627	472
R-sqd (%)	42.79	46.55	53.07	56.24	75.33	58.74	59.43	59.01	60.22	43.37	57.25	76.40

Monthly Fama-MacBeth cross-sectional regression with the bond yield spread as the dependent variable. The t-stats are reported in square brackets calculated using Fama-MacBeth standard errors with serial correlation corrected using Newey-West. The reported number of observations are the average number of observations per period. The reported R-squareds are the time-series averages of the cross-sectional R-squareds. γ is the monthly estimate of illiquidity measure using daily data. *Equity Vol* is estimated using daily equity returns of the bond issuer. *Age*, *Maturity*, *Issuance*, *Turnover*, *Trd Size*, and *#Trades* are as defined in Table 3. *Call Dummy* is one if the bond is callable and zero otherwise. Convertible and putable bonds are excluded from the regression. The sample period is from May 2003 through December 2008.

expected since both equity volatility and rating dummies are designed to control for the bond's fundamental risk.

When used simultaneously to explain the cross-sectional variation in bond yield spreads, both γ and equity volatility are significant, with the slope coefficients for both remaining more or less the same as before. This implies a limited interaction between the two variables, which is to be expected since the equity volatility is designed to pick up the fundamental information about a bond while γ is to capture its liquidity information. Moreover, the statistical significance of our illiquidity measure γ is virtually unchanged.

Taking advantage of the fact that a substantial sub-sample of our bonds have CDS traded on their issuers, we use CDS spreads as an additional control for the fundamental risk of a bond. We find a very strong relation between bond yields and CDS yields: the coefficient is 0.53 with a t-stat of 12.20. For the sub-sample of bonds with CDS traded, and controlling for the CDS spread, we still find a strong cross-sectional relation between our illiquidity measure γ and bond yields. The economic significance of the relation is smaller: a cross-sectional difference of γ of 1 translates to a 14 bps difference in bond yields. On the other hand, the statistical significance improves because the sample is less noisy.

Adding three bond characteristics — age, maturity and issuance — to compete with γ, we find that the positive connection between γ and average bond yield spreads remains robust. Both bond age and bond issuance are known to be linked to liquidity.[24] Our results show that bond age remains an important liquidity variable above and beyond our γ measure. In particular, a bond that is one year older is associated with an increase of 6 bps in average yield spreads.

Including the bond trading variables reveals that bonds with higher turnover and a large number of trades have higher average yield spreads. The slope coefficients for both variables are statistically significant. If one believes that more frequently traded bonds are more liquid, then this result would be puzzling. It is, however, arguable whether this variable actually captures the liquidity of a bond. We also find that bonds with higher average trade size have lower yield spreads. This result seems to be consistent with a liquidity explanation. Another possibility is that more frequent trades also reflect the speculative interest in the bonds, which can lead to higher yields. Overall, these variables are important control variables for us, since they are shown in Table 3 to be connected with our illiquidity measure γ. Our results show that these variables do not have a strong impact on the positive relation between our illiquidity

[24]See, for example, Houweling, Mentink, and Vorst (2003) and additional references therein.

measure γ and average yield spreads.

We also examine the relative importance of the quoted bid-ask spreads and our illiquidity measure γ. As shown in the last two columns of Table 5, the quoted bid-ask spreads are negatively related average yield spreads. Using both the quoted bid-ask spreads and our illiquidity measure γ, we find a robust result for γ and a statistically insignificant result for the quoted bid-ask spread. This aspect of our result is curious since Chen, Lesmond, and Wei (2007) report a positive relation between the quoted bid-ask spreads and yield spreads. We find that this discrepancy is due to both the junk bonds in our sample and to 2008 data.[25]

In unreported results, we also examine a subsample of investment grade bonds. Within this subsample, we find significant positive relation between yield spreads and quoted bid-ask spreads using pre-2008 data, but not when 2008 data is included. We also find that the coefficient of γ is somewhat smaller in this subsample (0.17 in the regression that corresponds to the fourth column of Table 5 as opposed to 0.21), but more statistically significant. This smaller coefficient could be a result of the fact that there is less variation in the yields of investment grade bonds. Furthermore, we find that equity volatility is less important in explaining the yields of investment grade bonds.

4 Further Analyses of Illiquidity

4.1 Dynamic Properties of Illiquidity

To further examine the dynamic properties of the transitory component in corporate bonds, we measure the autocovariance of price changes that are separated by a few trades or a few days:

$$\gamma_\tau = -\mathrm{Cov}\left(\Delta P_t, \Delta P_{t+\tau}\right). \tag{3}$$

The illiquidity measure we have used so far is simply γ_1. For $\tau > 1$, γ_τ measures the extent to which the mean-reversion persists after the initial price reversal at $\tau = 1$. In Table 6, we report the γ_τ for $\tau = 1, 2, 3$, using trade-by-trade data. Clearly, the initial bounce back is the strongest while the mean-reversion still persists after skipping a trade. In particular, γ_2 is on average 0.11 with a robust t-stat of 15.50. At the individual bond level, 74% of the bonds have a statistically significant γ_2. After skipping two trades, the amount of residual mean-reversion dissipates further in magnitude. The cross-sectional average of γ_3 is only 0.027, although it is

[25]This is not surprising given that the Phase I and II bonds in TRACE are predominantly investment grades, and the junk bonds covered by TRACE could be an unrepresentative pool.

still statistically significant with a robust t-stat of 11.60. At the individual bond level, fewer than 14% of the bonds have a statistically significant γ_3.

Table 6: **Dynamics of Illiquidity:** $\gamma_\tau = -\text{Cov}\left(P_t - P_{t-1}, P_{t+\tau} - P_{t+\tau-1}\right)$

		2003	2004	2005	2006	2007	2008	Full
$\tau = 1$	Mean γ	0.668	0.679	0.575	0.477	0.520	0.887	0.603
	Median γ	0.463	0.400	0.323	0.267	0.307	0.633	0.407
	Per t $\geq$ 1.96	99.35	97.56	99.63	99.59	99.52	98.06	99.83
	Robust t-stat	16.79	16.10	18.61	19.97	19.20	16.21	22.43
$\tau = 2$	Mean γ	0.084	0.068	0.079	0.056	0.105	0.341	0.106
	Median γ	0.038	0.025	0.032	0.027	0.060	0.211	0.061
	Per t $\geq$ 1.96	27.85	20.31	38.06	38.56	54.64	76.38	73.53
	Robust t-stat	10.36	7.61	12.73	10.08	13.47	14.23	15.50
$\tau = 3$	Mean γ	0.011	0.023	0.022	0.030	0.029	0.072	0.027
	Median γ	0.006	0.005	0.005	0.006	0.008	0.020	0.008
	Per t $\geq$ 1.96	4.92	5.75	6.77	8.25	6.76	11.51	13.78
	Robust t-stat	2.98	4.37	8.59	7.54	7.93	7.55	11.60

For each bond, its γ_τ, $\tau = 1, 2, 3$, is calculated using trade-by-trade data. Per t-stat $\geq$ 1.96 reports the percentage of bond with statistically significant γ. Robust t-stat is a test on the cross-sectional mean of γ with standard errors corrected for cross-sectional and time-series correlations.

The fact that the mean-reversion persists for a few trades before fully dissipating implies that autocovariance at the daily level is stronger than at the trade-by-trade level as it captures the effect cumulatively, as shown in Table 2. At the daily level, however, the mean-reversion dissipates rather quickly, with an insignificant γ_2 and γ_3. For brevity, we omit these results.

4.2 Asymmetry in Price Reversals

One interesting question regarding the mean-reversion captured in our main result is whether or not the magnitude of mean-reversion is symmetric in the sign of the initial price change. Specifically, with ΔP properly demeaned, let $\gamma^- = -Cov\left(\Delta P_t, \Delta P_{t+1} | \Delta P_t < 0\right)$ be a measure of mean-reversion conditioning on an initial price change that is negative, and let γ^+ be the counterpart conditioning on a positive price change. In a simple theory of liquidity based on costly market participation, Huang and Wang (2007) show that the bounce-back effect caused by illiquidity is more severe conditioning on an initial price movement that is negative, predicting a positive difference between γ^- and γ^+.

We test this hypothesis in Table 7, which shows that indeed there is a positive difference between γ^- and γ^+. Using trade-by-trade data, the cross-sectional average of $\gamma^- - \gamma^+$ is 0.1025

Table 7: **Asymmetry in γ**

Panel A: Using trade-by-trade data

Tau		2003	2004	2005	2006	2007	2008	Full
1	Mean	0.1547	0.0739	0.0120	0.0394	0.0679	0.1209	0.1025
	Median	0.1421	0.0183	-0.0064	0.0225	0.0627	0.1080	0.0556
	CS t-stat	8.42	3.90	0.92	3.36	5.62	6.76	7.79
	Robust t-stat	6.86	3.61	0.89	3.22	5.37	6.25	7.10
2	Mean	0.0379	0.0336	0.0428	0.0413	0.0542	0.0732	0.0488
	Median	0.0147	0.0078	0.0096	0.0169	0.0263	0.0519	0.0189
	CS t-stat	5.23	4.24	8.94	8.93	8.26	4.62	9.56
	Robust t-stat	5.21	3.94	7.79	7.59	7.65	4.38	8.74

Panel B: Using daily data

Tau		2003	2004	2005	2006	2007	2008	Full
1	Mean	0.2993	0.1726	0.1155	0.1240	0.1774	0.2046	0.1910
	Median	0.2006	0.0426	0.0171	0.0439	0.1031	0.1763	0.0892
	CS t-stat	10.64	5.47	5.06	5.79	6.30	2.74	9.89
	Robust t-stat	9.46	4.92	4.65	5.00	5.96	2.33	8.57
2	Mean	-0.0028	0.0043	0.0100	0.0003	0.0107	-0.0324	-0.0091
	Median	0.0002	0.0007	0.0011	0.0008	0.0003	0.0037	0.0007
	CS t-stat	-0.25	0.28	1.09	0.03	0.77	-0.59	-0.95
	Robust t-stat	-0.21	0.31	0.94	0.03	0.68	-0.47	-0.71

Asymmetry in γ is measured by the difference between γ^- and γ^+, where $\gamma^- = -E\left(\Delta P_{t+1}\Delta P_t | \Delta P_t < 0\right)$, with ΔP properly demeaned, measures the price reversal conditioning on a negative price movement. Likewise, γ^+ measures the price reversal conditioning on a positive price movement. Robust t-stat is a pooled test on the mean of $\gamma^- - \gamma^+$ with standard errors clustered by bond and day. CS t-stat is the cross-sectional t-stat.

with a robust t-stat of 7.10. Skipping a trade, the asymmetry in γ_2 is on average 0.0488 with a robust t-stat of 8.74. Compared with how γ_τ dissipates across τ, this measure of asymmetry does not exhibit the same dissipating pattern. In fact, in the later sample period, the level of asymmetry for $\tau = 2$ is almost as important for the first-order mean-reversion, with an even higher statistical significance. Using daily data, the asymmetry is stronger, incorporating the cumulative effect from the transaction level. The cross-sectional average of $\gamma^- - \gamma^+$ is 0.19, which is close to 20% of the observed level of mean reversion. Skipping a day, however, produces no evidence of asymmetry, which is expected since there is very little evidence of mean-reversion at this level in the first place.

4.3 Trade Size and Illiquidity

Since our illiquidity measure is based on transaction prices, a natural question is how it is related to the sizes of these transactions. In particular, are reversals in price changes stronger for trades of larger or smaller sizes? In order to answer this question, we consider the autocovariance of price changes conditional on different trade sizes.

For a change in price $P_t - P_{t-1}$, let V_t denote the size of the trade associated with price P_t. The autocovariance of price changes conditional on trade size being in a particular range, say, R, is defined as

$$\text{Cov}\left(P_t - P_{t-1}, P_{t+1} - P_t, \,\middle|\, V_t \in R\right) , \tag{4}$$

where six brackets of trade sizes are considered in our estimation: (\$0, \$5K], (\$5K, \$15K], (\$15K, \$25K], (\$25K, \$75K], (\$75K, \$500K], and (\$500K, ∞), respectively. Our choice of the number of brackets and their respective cutoffs is influenced by the sample distribution of trade sizes. In particular, to facilitate the estimation of γ conditional on trade size, we need to have enough transactions within each bracket for each bond to obtain a reliable conditional γ.

For the same reason, we construct our conditional γ using trade-by-trade data. Otherwise, the data would be cut too thin at the daily level to provide reliable estimates of conditional γ. For each bond, we categorize transactions by their time-t trade sizes into their respective bracket s, with $s = 1, 2, \ldots, 6$, and collect the corresponding pairs of price changes, $P_t - P_{t-1}$ and $P_{t+1} - P_t$. Grouping such pairs of prices changes for each size bracket s and for each bond, we can estimate the autocovariance of the price changes, the negative of which is our conditional $\gamma(s)$.[26]

Equipped with the conditional γ, we can now explore the link between trade size and illiquidity. In particular, does $\gamma(s)$ vary with s and how? We answer this question by first controlling for the overall liquidity of the bond. This control is important as we find in Section 3.2 that the average trade size of a bond is an important determinant of the cross-sectional variation of γ. So we first sort all bonds by their unconditional γ into quintiles and then examine the connection between $\gamma(s)$ and s within each quintile.

As shown in Panel A of Table 8, for each γ quintile, there is a pattern of decreasing conditional γ with increasing trade size and the relation is monotonic for all γ quintiles. For example, quintile 1 consists of bonds with the highest γ and therefore the least liquid in our sample. The mean γ is 2.13 for trade-size bracket 1 (less than \$5K) but it decreases to 0.69

[26]Specifically, we compute six conditional covariances for each bond, one for each size bracket. The negative of these conditional covariances is our conditional γ.

for trade-size bracket 6 (greater than \$500K). The mean difference in γ between the trade-size bracket 1 and 6 is 1.37 and has a robust t-stat of 9.22. Likewise, for quintile 5, which consists of bonds with the lowest γ measure and therefore are the most liquid, the same pattern emerges. The average value of γ is 0.23 for the smallest trades and then decreases monotonically to 0.02 for the largest trades. The difference between the two is 0.21, with a robust t-stat of 8.20, indicating that the conditional γ between small and large size trades remains significant even for the most liquid bonds. To check the potential impact of outliers, we also report the median γ for different trade sizes. Although the magnitudes are slightly smaller, the general pattern remains the same.

Table 8: **Variation of γ with Trade Size**

γ Quint	trade size =	1	2	3	4	5	6	1 - 6
1	Mean	2.13	1.64	1.47	1.29	0.89	0.69	1.37
	Median	1.94	1.53	1.40	1.25	0.84	0.53	1.26
	Robust t-stat	13.14	10.64	9.73	9.56	8.51	6.17	9.22
2	Mean	1.13	0.93	0.83	0.67	0.38	0.24	0.88
	Median	1.05	0.86	0.78	0.62	0.36	0.19	0.82
	Robust t-stat	10.59	10.16	10.60	11.65	13.92	10.15	8.54
3	Mean	0.69	0.56	0.49	0.38	0.22	0.12	0.57
	Median	0.61	0.51	0.45	0.36	0.21	0.10	0.48
	Robust t-stat	8.32	12.26	12.17	12.58	14.19	11.29	7.05
4	Mean	0.43	0.34	0.28	0.20	0.12	0.06	0.37
	Median	0.37	0.30	0.25	0.19	0.11	0.05	0.31
	Robust t-stat	8.69	12.23	12.20	13.31	15.57	11.25	7.64
5	Mean	0.23	0.17	0.14	0.10	0.05	0.02	0.21
	Median	0.21	0.17	0.13	0.09	0.05	0.02	0.18
	Robust t-stat	8.93	13.95	12.41	15.76	18.35	13.23	8.20

Trade size is categorized into 6 groups with cutoffs of \$5K, \$15K, \$25K, \$75K, and \$500K. $\gamma = -\mathrm{Cov}(P_t - P_{t-1}, P_{t+1} - P_t)$. γ is calculated conditioning on the trade size associated with P_t. Bonds are sorted by their "unconditional" γ into quintiles, and the variation of γ by trade size is reported for each quintile group. The trade-by-trade data is used in the calculation. For the daily data, the results are similar but stronger.

Overall, our results demonstrate a clear negative relation between trade sizes and our illiquidity measure.[27] The interpretation of this result, however, requires caution. It would be simplistic to infer from this pattern that larger trades face less illiquidity or have less impact

[27]In the Appendix, we consider an alternative method of examining γ by trade size, simply cutting the data into trade size brackets and calculating γ separately for each bracket. We find a similar negative relation between trade sizes and our illiquidity measure using this methodology.

on prices. It is important to realize that both trades sizes and prices are endogenous variables. Their relation arises from an equilibrium outcome in which traders of different types optimally choose their trading strategies, taking into account the dynamics of the market including the actions of their own and others. Non-competitive factors such as negotiation power for large trades can also contribute to the relation between trade sizes and γ.

5 Illiquidity and Bid-Ask Spread

It is well known that the bid-ask spread can lead to negative autocovariance in price changes. For example, using a simple specification, Roll (1984) shows that when transactions prices bounce between bid and ask prices, depending on whether they are sell or buy orders from customers, their changes exhibit negative autocovariance even when the "underlying value" follows a random walk. Thus, it is important to ask whether or not the negative autocovariances documented in this paper are simply a reflection of bid-ask bounce. Using quoted bid-ask spreads, we show in Table 2 that the associated bid-ask bounce can only generate a tiny fraction of the empirically observed autocovariance in corporate bonds. Quoted spreads, however, are mostly indicative rather than binding. Moreover, the structure of the corporate bond market is mostly over-the-counter, making it even more difficult to estimate the actual bid-ask spreads.[28] Thus, a direct examination of how bid-ask spreads contribute to our illiquidity measure γ is challenging.

We can, however, address this question to certain extent by taking advantage of the results by Edwards, Harris, and Piwowar (2007) (EHP hereafter). Using a more detailed version of the TRACE data that includes the side on which the dealer participated, they provide estimates of effective bid-ask spreads for corporate bonds. To examine the extent to which our illiquidity measure γ can be explained by the estimated bid-ask spread, we use our illiquidity measure γ to compute the implied bid-ask spreads, and compare them with the estimated bid-ask spreads reported by EHP. The actual comparison will not be exact, since our sample of bonds is different from theirs. Later in the section, we will discuss how this could affect our analysis.

It is first instructive to understand the theoretical underpinning of how our estimate of γ relates to the estimate of bid-ask spreads in EHP. In the Roll (1984) model, the transaction price P_t takes the form of equation (1), in which P is the sum of the fundamental value and a

[28]The corporate bond market actually involves different trading platforms, which provide liquidity to different clienteles. In such a market, a single bid-ask spread can be too simplistic in capturing the actual spreads in the market.

transitory component. Moreover, the transitory component equals to $\frac{1}{2} S\, q_t$ in the Roll model, with S being the bid-ask spread and q_t indicating the direction of trade. Specifically, q is $+1$ if the transaction is buyer initiated and -1 if it is seller initiated, assuming that the dealer takes the other side. More specifically, in the Roll model, we have

$$P_t = F_t + \tfrac{1}{2} S\, q_t\,. \tag{5}$$

If we further assume that q_t is *i.i.d.* over time, the autocovariance in price change then becomes $-(S/2)^2$, or $\gamma = (S/2)^2$. Conversely, we have

$$S_{\text{Roll}} = 2\sqrt{\gamma}\,, \tag{6}$$

where we call S_{Roll} the implied bid-ask spread.

EHP use an enriched Roll model, which allows the spreads to depend on trade sizes. In particular, they assume

$$P_t = F_t + \tfrac{1}{2} S(V_t)\, q_t\,, \tag{7}$$

where V_t is the size of the trade at time t.[29] Since the dataset used by EHP also contains information about q_t, they directly estimate the first difference of equation (7), assuming a factor model for the increments of F_t.

Table 9 reproduces the results of EHP, who estimate percentage bid-ask spreads for average trade sizes of \$5K, \$10K, \$20K, \$50K, \$100K, \$200K, \$500K and \$1M. The cross-sectional medians of the percentage bid-ask spreads are 1.20%, 1.12%, 96 bps, 66 bps, 48 bps, 34 bps, 20 bps and 12 bps, respectively. To compare with their results, we form trade size brackets that center around their reported trade sizes. For example, to compare with their trade size \$10K, we calculate our illiquidity measure γ conditional on trade sizes falling between \$7.5K and \$15K, and then calculate the implied bid-ask spread. Using the average price for the respective bond, we further convert the spread to percentage spread so as to compare with the EHP result. The results are reported in Table 9, where to correct for the difference in our respective sample periods, we also report our implied bid-ask spreads for the period used by EHP. For the EHP sample period, the cross-sectional medians of our implied percentage bid-ask spreads are 1.82%, 1.80%, 1.59%, 1.23%, 91 bps, 68 bps, 57 bps, and 54 bps, respectively.

[29] The model EHP use has an additional feature. It distinguishes customer-dealer trades from dealer-dealer trades. The spread they estimate is for the customer-dealer trades. Thus, in (7), we simply do not identify dealer-dealer trades. This decreases our estimate of γ relative to EHP since we are including inter-dealer trades which have a smaller spread than customer-dealer trades.

Table 9: **Implied and Estimated Bid-Ask Spreads**

	Full Sample Period			EHP Subperiod					
	γ-Implied			γ-Implied			EHP Estimated		
trade size	#bonds	Mean	Med	#bonds	Mean	Med	EHP Size	Mean	Med
$\leq$ 7,500	1,148	2.21	1.90	938	2.07	1.82	5K	1.50	1.20
(7500, 15K]	1,156	1.98	1.73	1,036	1.98	1.80	10K	1.42	1.12
(15K, 35K]	1,160	1.80	1.50	1,043	1.80	1.59	20K	1.24	0.96
(35K, 75K]	1,152	1.56	1.25	906	1.38	1.23	50K	0.92	0.66
(75K, 150K]	1,124	1.28	1.02	817	1.00	0.91	100K	0.68	0.48
(150K, 350K]	1,025	0.94	0.76	678	0.68	0.68	200K	0.48	0.34
(350K, 750K]	1,066	0.82	0.69	786	0.60	0.57	500K	0.28	0.20
> 750K	1,093	0.74	0.61	950	0.52	0.54	1,000K	0.18	0.12

The bid-ask spreads are calculated as a percentage of the market value of the bond and are reported in percentages. The EHP bid-ask spread estimates are from Table 4 of Edwards, Harris, and Piwowar (2007), and the EHP subperiod is Jan. 2003 to Jan. 2005. Our bid-ask spreads are obtained using Roll's measure: $2\sqrt{\gamma}$ divided by the average market value of the bond. The sample of bonds differs from that in EHP, and our selection criteria biases us toward more liquid bonds with smaller bid-ask spreads.

As we move on to compare our median estimates to those in EHP, it should be mentioned that this is a simple comparison by magnitudes, not a formal statistical test.

Overall, our implied spreads are much higher than those estimated by EHP. For small trades, our median estimates of implied spreads are over 50% higher than those by EHP. Moving to larger trades, the difference becomes even more substantial. Our median estimates are close to doubling theirs for the average sizes of \$100K and \$200K, close to tripling theirs for the average size of \$500K, and more than quadrupling theirs for the average size of \$1,000K. In fact, our estimates are biased downward for the trade size group around \$1,000K, since our estimated bid-ask spreads include all trade sizes above \$750K, including trade sizes of \$2M, \$5M, and \$10M, whose median bid-ask spreads are estimated by EHP to be 6 bps, 2 bps, and 2 bps, respectively. We have to group such trade sizes because in the publicly available TRACE data, the reported trade size is truncated at \$1M for speculative grade bonds and at \$5M for investment grade bonds.

In addition to differing in sample periods, which is easy to correct, our sample is also different from that used in EHP in the composition of the bonds that are used to estimate the bid-ask spreads. In particular, our selection criteria bias our sample towards highly liquid bonds. For example, to be included in our sample, the bond has to trade at least 75% of business days, while the median frequency of days with a trade is only 48% for the bonds used in EHP. The median average trade sizes is \$462K in 2003 and \$401K in 2004 for the bonds used in our sample, compared with \$240K for the bonds used in EHP; the median average number of trades per month is 148 in 2003 and 122 in 2004 for the bonds in our sample, while the median average number of trades per day is 1.1 for the bonds used in EHP. Given that more liquid bonds typically have smaller bid-ask spreads, the difference between our implied bid-ask spreads and EHP's estimates would have been even more drastic had we been able to match our sample of bonds to theirs. It is therefore our conclusion that the negative autocovariance in price changes observed in the bond market is much more substantial than merely the bid-ask effect. And our measure of illiquidity captures more broadly the impact of illiquidity in the market.

Finally, one might be curious as to what is the exact mechanism that drives our estimates apart from those by EHP. Within the Roll model as specified in equation (6), our estimates should be identical to theirs. In particular, using equation (5) to identify bid-ask spread S implies regressing ΔP_t on Δq_t. But using our model specified in equation (1) as a reference, it is possible that the transitory component u_t does not take the simple form of $\frac{1}{2}\,S\,q_t$. More specifically, the residual of this regression of ΔP_t on Δq_t might still exhibit a high degree of negative autocovariance, simply because u_t is not fully captured by $\frac{1}{2}\,S\,q_t$. If that is true, then our measure of illiquidity captures the transitory component more completely: both the bid-ask bounce associated with $\frac{1}{2}\,S\,q_t$ and the additional mean-reversion that is not related to bid-ask bounce. Overall, more analysis is needed, possibly with more detailed data as in EHP, in order to fully reconcile the two sets of results.[30]

6 Conclusions

The main objective of our paper is to gauge the level of illiquidity in the corporate bond market and to examine its key properties and implications. Using a theoretically motivated measure of illiquidity, i.e., the amount of price reversals as captured by the negative of autocovariance of prices changes, we show that this illiquidity measure is both statistically and economically significant for a broad cross-section of corporate bonds examined in this paper. We demonstrate that the magnitude of the reversals is beyond what can be explained by bid-ask bounce. We also show that the reversals exhibit significant asymmetry: price reversals are on average stronger after a price reduction than a price increase.

[30] In general, liquidity in the market depends who is trading, why and how. The additional information in the data used by EHP allows more differentiation of these factors. The TRACE data, however, is more coarse and does not allow us to fully identify the source of the different between our measures of implied spreads and the estimated spreads of EHP.

We find that a bond's illiquidity is related to several bond characteristics. In particular, illiquidity increases with a bond's age and maturity, but decreases with its rating and issue size. As compared to a bond's idiosyncratic return volatility, a bond's illiquidity shows limited relation with its market risk exposures, as measured by its beta with respect to the stock and bond market indices. We also find that price reversals are inversely related to trade sizes. That is, prices changes accompanied by small trades exhibit stronger reversals than those accompanied by large trades.

Furthermore, the illiquidity of individual bonds fluctuates substantially over time. More interestingly, these time fluctuations display important commonalities. For example, the median illiquidity over all bonds, which represents a market-wide illiquidity, increases sharply during the periods of market turmoil such as the downgrade of Ford and GM to junk status around May of 2005, the sub-prime market crisis starting in August 2007, and in late 2008 when Lehman filed for bankruptcy. Exploring the relation between changes in the market-wide illiquidity and other market variables, we find that changes in illiquidity are positively related to changes in VIX and that this relation is not driven solely by the events in 2008. During pre-2008 periods, we also find that aggregate illiquidity tends to rise following down markets.

We also find important pricing implications associated with bond illiquidity. Our result shows that for two bonds in the same rating category, a one-standard-deviation difference in their illiquidity measure would set their yield spreads apart by 37 bps. This result remains robust in economic and statistical significance, after controlling for bond fundamental information and bond characteristics including those commonly related to bond liquidity.

Our results raise several questions concerning the liquidity of corporate bonds. First, what are the underlying factors giving rise to the high level of illiquidity? This question is particularly pressing when we contrast the magnitude of our illiquidity measure in the corporate bond market against that in the equity market. Second, what causes the fluctuations in the overall level of illiquidity in the market? Are these fluctuations merely another manifestation of more fundamental risks or a reflection of new sources of risks such as a liquidity risk? Third, does the high level of illiquidity for the corporate bonds indicate any inefficiencies in the market? If so, what would be the policy remedies? We leave these questions for future work.

Appendix

A Measure of Illiquidity, Log Price Changes

In Table 10, we reproduce the results in Table 2, but use changes in log prices. In particular, we define γ as

$$\gamma = -\text{Cov}\left(\Delta Ln(P_t), \Delta Ln(P_{t+1})\right). \tag{8}$$

Note that reported γ's are scaled by 10,000 for easier comparison with γ's calculated using ΔP.

Throughout the main text of the paper, γ is calculated using price changes rather than returns. Here and in some of the analyses below, we consider the robustness of our main results to log returns by using changes in log prices to construct γ.

B Time Variation in Gamma

In Table 11, we present regression results for determinants of the aggregate γ. This table corresponds to Panel A of Table 4, but with γ calculated using log price changes rather than price changes.

C Cross-Sectional Determinants of Yield Spreads

We report results using log price changes rather than price changes in Table 12. Our results remain largely unchanged. In Table 13, we consider only the subset of non-callable bonds. As callable bonds of the poorest credit quality are unlikely to be called, bond age may actually be a proxy for credit quality in a sample of callable bonds. We find that in the subsample of non-callable bonds, age remains an important determinant of yield spread.

D Gamma by Trade Size

In Table 14, we consider γ calculated using only trades of certain sizes. First, we take all trades for a particular bond and sort these trades by into the smallest 30% of trade size, middle 40%, and largest 30%. We then calculate γ using only trades from a given bin to estimate small trade, medium trade, and large trade γ's. These results are supplemental to those presented in Table 8, but provide an additional robustness check as these γ's are calculated solely with a subset of trades of a given size rather than conditioning on the trade size at t as in equation (4). Furthermore, the size of trades is now grouped relative to a bond's other trades rather than with respect to a fixed cut-off.

Table 10: **Measure of Illiquidity** $\gamma = -\text{Cov}\left(lnP_t - lnP_{t-1}, lnP_{t+1} - lnP_t\right)$

Panel A: Individual Bonds	2003	2004	2005	2006	2007	2008	Full
Trade-by-Trade Data							
Mean γ	0.65	0.68	0.63	0.53	0.56	1.45	0.70
Median γ	0.41	0.36	0.30	0.27	0.30	0.70	0.39
Per t $\geq$ 1.96	99.35	97.38	99.63	99.59	99.52	97.91	99.83
Pooled t-stat	15.01	15.07	17.81	19.52	18.22	12.85	20.21
Daily Data							
Mean γ	1.01	1.06	1.01	0.88	1.05	5.05	1.38
Median γ	0.62	0.50	0.44	0.40	0.60	1.74	0.65
Per t $\geq$ 1.96	94.29	90.08	95.33	96.48	94.66	90.85	97.93
Pooled t-stat	17.74	12.84	21.50	21.92	19.36	10.22	18.32

Panel B: Bond Portfolios	2003	2004	2005	2006	2007	2008	Full
Equal-weighted	-0.0010	-0.0037	-0.0031	0.0010	-0.0005	-0.1222	-0.0239
t-stat	-0.20	-1.06	-0.93	0.79	-0.21	-1.37	-1.44
Issuance-weighted	0.0021	-0.0035	-0.0012	0.0007	0.0004	-0.1361	-0.0249
t-stat	0.36	-0.97	-0.32	0.47	0.13	-1.77	-1.74

Panel C: Implied by Quoted Bid-Ask Spreads	2003	2004	2005	2006	2007	2008	Full
Mean implied γ	0.045	0.041	0.061	0.058	0.058	0.084	0.052
Median implied γ	0.032	0.027	0.026	0.025	0.026	0.052	0.030

At the individual bond level, γ is calculated using either trade-by-trade or daily data. γ is scaled by 10,000. Per t-stat $\geq$ 1.96 reports the percentage of bond with statistically significant γ. Robust t-stat is a test on the cross-sectional mean of γ with standard errors corrected for cross-sectional and time-series correlations. At the portfolio level, γ is calculated using daily data and the Newey-West t-stats are reported. Monthly quoted bid-ask spreads, which we have data for 1,170 out of 1,205 bonds in our sample, are used to calculate the implied γ.

Table 11: **Time Variation in γ and Market Variables, Ln Prices**

Cons	0.0346	0.0084	0.0031	0.0404	0.0401	0.0366	0.0305	0.0148
	[1.05]	[0.75]	[0.35]	[1.06]	[1.08]	[1.16]	[1.29]	[1.07]
Δ VIX	0.0578							0.0599
	[5.51]							[4.32]
Δ Bond Volatility		0.0482						0.0348
		[1.92]						[3.01]
Δ CDS Index			0.3501					-0.0624
			[1.63]					[-0.51]
Δ Term Spread				0.6092				
				[1.35]				
Δ Default Spread					-0.0767			
					[-0.39]			
Lagged Stock Return						-0.0073		
						[-0.54]		
Lagged Bond Return							-0.0544	
							[-1.51]	
Adj R-sqd (%)	63.54	2.53	12.18	11.63	-1.17	-0.80	7.43	65.30

Monthly changes in γ regressed on monthly changes in bond index volatility, VIX, CDS index, term spread, default spread, and lagged stock and bond returns. The Newey-West t-stats are reported in square brackets. Regressions with CDS Index do not include 2003 data. γ is calculated using log price changes and is scaled by 10,000.

Table 12: **Bond Yield Spread and Illiquidity Measure γ, ln P**

Cons	1.13	0.97	-0.70	-0.58	0.14	-0.34	-0.64	-0.05	-1.21	1.66	-0.23	0.26
	[3.46]	[3.14]	[-1.55]	[-1.52]	[0.95]	[-1.30]	[-2.08]	[-0.22]	[-2.72]	[2.11]	[-1.11]	[2.77]
γ		0.22		0.22	0.12	0.17	0.17	0.16	0.16		0.21	0.10
		[4.45]		[5.14]	[3.75]	[3.70]	[3.83]	[3.52]	[3.65]		[4.80]	[3.12]
Equity Vol			0.06	0.05	0.02	0.05	0.05	0.05	0.05		0.05	0.02
			[3.82]	[3.51]	[3.67]	[3.53]	[3.48]	[3.55]	[3.42]		[3.72]	[3.65]
CDS Spread					0.52							0.52
					[11.16]							[10.96]
Age						0.05	0.06	0.04	0.06			
						[2.54]	[3.07]	[2.36]	[2.70]			
Maturity						-0.00	-0.00	-0.00	-0.00			
						[-0.11]	[-0.18]	[-0.16]	[-0.08]			
ln(Issuance)						-0.07	-0.05	-0.03	-0.16			
						[-2.13]	[-1.76]	[-1.24]	[-3.51]			
Turnover							0.03					
							[5.27]					
ln(Trd Size)								-0.10				
								[-2.52]				
ln(#Trades)									0.29			
									[5.12]			
Quoted B/A Spread										-1.34	-0.87	-0.21
										[-1.09]	[-1.14]	[-0.52]
Call Dummy	-0.44	-0.44	0.12	0.07	0.04	0.08	0.10	0.09	0.12	-0.38	0.19	0.08
	[-1.05]	[-1.07]	[2.14]	[1.65]	[1.11]	[1.79]	[2.30]	[1.75]	[2.33]	[-1.11]	[1.57]	[1.22]
A Dummy	0.69	0.66	0.19	0.18	0.24	0.18	0.17	0.19	0.24	0.67	0.11	0.20
	[1.52]	[1.52]	[1.14]	[1.17]	[1.50]	[1.14]	[1.07]	[1.24]	[1.43]	[1.56]	[1.08]	[1.71]
BAA Dummy	1.19	1.07	0.74	0.69	0.56	0.67	0.61	0.72	0.77	1.18	0.67	0.56
	[2.85]	[2.89]	[2.77]	[2.69]	[2.45]	[2.46]	[2.16]	[2.59]	[2.52]	[3.15]	[3.31]	[2.68]
Junk Dummy	5.41	4.65	3.86	3.39	1.28	3.37	3.33	3.42	3.45	5.43	3.43	1.35
	[4.38]	[4.46]	[3.96]	[3.94]	[4.29]	[4.04]	[3.98]	[4.02]	[4.02]	[3.97]	[3.74]	[3.62]
Obs	679	670	679	670	502	670	670	670	670	633	627	472
R-sqd (%)	42.79	49.80	53.07	58.22	76.06	60.66	61.33	60.91	62.02	43.37	59.22	77.21

Monthly Fama-MacBeth cross-sectional regression with the bond yield spread as the dependent variable. The t-stats are reported in square brackets calculated using Fama-MacBeth standard errors with serial correlation corrected using Newey-West. The reported number of observations are the average number of observations per period. The reported R-squareds are the time-series averages of the cross-sectional R-squareds. γ is the monthly estimate of illiquidity measure using daily data and log price changes. *Equity Vol* is estimated using daily equity returns of the bond issuer. *Age*, *Maturity*, *Issuance*, *Turnover*, *Trd Size*, and *#Trades* are as defined in Table 3. *Call Dummy* is one if the bond is callable and zero otherwise. Convertible and putable bonds are excluded from the regression. The sample period is from May 2003 through December 2008.

Table 13: **Bond Yield Spread and Illiquidity Measure γ, Non-Callable Only**

Cons	0.98	0.91	-0.41	-0.40	-0.06	-1.59	-2.11	-1.73	-1.92	1.55	-0.03	0.23
	[3.86]	[3.63]	[-0.95]	[-0.96]	[-0.27]	[-2.84]	[-2.72]	[-2.64]	[-2.77]	[1.87]	[-0.15]	[0.83]
γ		0.13		0.14	0.13	0.06	0.07	0.06	0.06		0.12	0.12
		[6.59]		[9.92]	[6.95]	[2.96]	[3.22]	[3.03]	[2.44]		[6.72]	[7.21]
Equity Vol			0.04	0.04	0.03	0.04	0.04	0.04	0.04		0.04	0.03
			[3.31]	[3.05]	[2.01]	[2.99]	[2.92]	[2.98]	[2.92]		[3.05]	[1.95]
CDS Spread					0.54							0.54
					[27.58]							[23.31]
Age						0.08	0.10	0.09	0.09			
						[2.86]	[3.07]	[2.77]	[2.93]			
Maturity						0.00	0.00	-0.00	0.01			
						[0.02]	[0.07]	[-0.02]	[0.28]			
ln(Issuance)						0.11	0.15	0.11	-0.07			
						[4.02]	[4.33]	[3.16]	[-1.25]			
Turnover							0.04					
							[3.02]					
ln(Trd Size)								0.04				
								[0.63]				
ln(#Trades)									0.29			
									[3.72]			
Quoted B/A Spread										-1.29	-0.66	-0.58
										[-0.83]	[-0.74]	[-0.85]
A Dummy	1.16	1.10	0.22	0.17	0.25	0.23	0.25	0.21	0.28	1.12	0.10	0.19
	[1.49]	[1.48]	[1.68]	[1.72]	[1.07]	[1.88]	[1.83]	[1.91]	[2.13]	[1.48]	[1.47]	[1.04]
BAA Dummy	1.44	1.38	0.98	0.89	0.56	0.85	0.78	0.83	0.87	1.42	0.87	0.58
	[3.16]	[2.90]	[3.74]	[3.65]	[2.00]	[2.77]	[2.60]	[2.78]	[2.65]	[3.00]	[3.51]	[1.89]
Junk Dummy	6.24	4.31	5.38	3.53	1.21	3.48	3.45	3.48	3.45	6.33	3.41	1.30
	[3.76]	[3.25]	[3.50]	[3.05]	[3.52]	[3.01]	[2.97]	[3.02]	[2.97]	[3.33]	[2.85]	[3.14]
Obs	373	370	373	370	283	370	370	370	370	357	356	273
R-sqd (%)	44.43	44.62	52.57	52.40	72.22	56.82	57.97	57.11	58.30	46.10	53.61	73.70

Monthly Fama-MacBeth cross-sectional regression with the bond yield spread as the dependent variable. The t-stats are reported in square brackets calculated using Fama-MacBeth standard errors with serial correlation corrected using Newey-West. The reported number of observations are the average number of observations per period. The reported R-squareds are the time-series averages of the cross-sectional R-squareds. γ is the monthly estimate of illiquidity measure using daily data. *Equity Vol* is estimated using daily equity returns of the bond issuer. *Age*, *Maturity*, *Issuance*, *Turnover*, *Trd Size*, and *#Trades* are as defined in Table 3. Callable, convertible and putable bonds are excluded from the regression. The sample period is from May 2003 through December 2008.

Table 14: γ **by Trade Size**

Panel A: Using Trade-by-Trade Data								
Trade Size		2003	2004	2005	2006	2007	2008	Full
Small	Mean γ	1.10	1.05	0.83	0.72	0.77	1.18	0.88
	Median γ	0.76	0.62	0.48	0.41	0.45	0.76	0.59
	Per t $\geq$ 1.96	91.32	90.43	95.48	94.62	92.23	88.11	99.09
	Robust t-stat	13.54	14.35	17.47	17.90	17.00	15.34	20.62
Medium	Mean γ	0.69	0.68	0.58	0.47	0.48	0.78	0.57
	Median γ	0.48	0.43	0.33	0.25	0.25	0.53	0.39
	Per t $\geq$ 1.96	95.84	92.40	96.60	96.27	95.16	91.29	97.75
	Robust t-stat	14.91	16.37	17.20	19.20	18.02	15.05	22.11
Large	Mean γ	0.29	0.30	0.27	0.22	0.25	0.47	0.27
	Median γ	0.11	0.08	0.07	0.06	0.08	0.24	0.10
	Per t $\geq$ 1.96	90.13	83.94	90.02	85.42	82.93	79.03	95.35
	Robust t-stat	13.44	12.65	14.20	13.68	13.51	12.82	17.42
Panel B: Using Daily Data								
Trade Size		2003	2004	2005	2006	2007	2008	Full
Small	Mean γ	1.55	1.41	1.26	1.04	1.30	2.92	1.44
	Median γ	1.05	0.80	0.68	0.59	0.84	2.03	0.98
	Per t $\geq$ 1.96	86.14	83.24	90.22	89.52	89.03	83.59	96.75
	Robust t-stat	21.04	16.29	24.26	24.20	20.76	17.37	25.84
Medium	Mean γ	1.02	0.92	0.83	0.65	0.76	2.05	0.91
	Median γ	0.65	0.54	0.45	0.32	0.40	1.22	0.58
	Per t $\geq$1.96	89.88	86.18	92.51	91.16	89.62	86.33	95.58
	Robust t-stat	23.26	18.72	24.45	22.30	20.34	15.22	27.66
Large	Mean γ	0.50	0.46	0.42	0.35	0.47	1.20	0.47
	Median γ	0.18	0.12	0.10	0.07	0.12	0.48	0.15
	Per t $\geq$1.96	68.59	63.04	70.93	71.18	69.33	63.08	80.33
	Robust t-stat	14.28	13.05	15.30	14.27	9.84	9.53	17.84

γ is calculated using only trades of sizes in the smallest 30%, middle 40%, or largest 30% for each bond. Per t-stat $\geq$ 1.96 reports the percentage of bond with statistically significant γ. Robust t-stat is a test on the cross-sectional mean of γ with standard errors corrected for cross-sectional and time-series correlations.

References

Bao, J. and J. Pan (2008). Excess Volatiity of Corporate Bonds. Working Paper, MIT Sloan.

Bessembinder, H., W. Maxwell, and K. Venkataraman (2006). Optimal Market Transparency: Evidence from the Initiation of Trade Reporting in Corporate Bonds. *Journal of Financial Economics 82*, 251–288.

Chen, L., D. Lesmond, and J. Wei (2007). Coporate Yield Spreads and Bond Liquidity. *Journal of Finance 62*, 119–149.

Chordia, T., R. Roll, and A. Subrahmanyam (2000). Commonality in Liquidity. *Journal of Financial Economics 56*, 3–28.

Colin-Dufresne, P., R. Goldstein, and J. S. Martin (2001). The Determinants of Credit Spread Changes. *Journal of Finance 56*, 2177–2207.

de Jong, F. and J. Driessen (2005). Liquidity Risk Premia in Corporate Bond Markets. Working Paper, University of Amsterdam.

Downing, C., S. Underwood, and Y. Xing (2005). Is Liquidity Risk Priced in the Corporate Bond Market? Working Paper, Rice University.

Edwards, A. K., L. E. Harris, and M. S. Piwowar (2007). Corporate bond market transaction costs and transparency. *Journal of Finance 62*, 1421–1451.

Goldstein, M. A., E. S. Hotchkiss, and E. R. Sirri (2007). Transparency and Liquidity: A Controlled Experiment on Corporate Bonds. *Review of Financial Studies 20*, 235–273.

Grossman, S. and M. Miller (1988). Liquidity and Market Structure. *Journal of Finance 38*, 617–633.

Harris, L. (1990). Statistical Properties of the Roll Serial Covariance Bid/Ask Spread Estimator. *The Journal of Finance 45*, 579–590.

Houweling, P., A. Mentink, and T. Vorst (2003). How to Measure Corporate Bond Liquidity? Working Paper, Erasmus University Rotterdam.

Huang, J. and M. Huang (2003). How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk? Working Paper, Penn State and Cornell.

Huang, J. C. and J. Wang (2007). Liquidity and Market Crashes. *Review of Financial Studies*, forthcoming.

Khang, K. and T.-H. D. King (2004). Return reversals in the bond market: evidence and causes. *Journal of Banking and Finance 28*, 569—593.

Longstaff, F., S. Mithal, and E. Neis (2005). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default Swap Market. *Journal of Finance 60*, 2213–2253.

Mahanti, S., A. Nashikkar, and M. Subrahmanyam (2008). Latent Liquidity and Corporate Bond Yield Spreads. Working Paper, New York University.

Nashikkar, A., S. Mahanti, M. Subrahmanyam, G. Chacko, and G. Mallik (2008). Latent Liquidity: A New Measure of Liquidity, with an Application to Corporate Bonds. *Journal of Financial Economics 88*, 272–298.

Newey, W. K. and K. D. West (1987). A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica 29*, 229–256.

Niederhoffer, V. and M. F. M. Osborne (1966). Market Making and Reversal of the Stock Exchange. *Journal of the American Statistical Association 61*, 897–916.

Pastor, L. and R. F. Stambaugh (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy 111*, 642–685.

Roll, R. (1984). A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *Journal of Finance 39*, 1127–1139.

Vayanos, D. and J. Wang (2009). Liquidity and Asset Prices: A Unified Framework. Working Paper, LSE and MIT.