# Liquidity Risk of Corporate Bond Returns

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**Abstract**

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KEYWORDS: CREDIT RISK, CREDIT SPREADS, DEFAULT, RECESSION, FLIGHT TO LIQUIDITY.

JEL CLASSIFICATIONS: G12, G13, G32, G33.

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## Abstract

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Keywords: credit risk, credit spreads, default, recession, flight to quality.

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# 1 Introduction

Liquidity shocks affect asset prices because asset liquidity affects expected returns of both stocks and bonds (Amihud and Mendelson, 1986, 1991). Because asset illiquidity is stationary (highly autoregressive), an unexpected rise in illiquidity raises expected illiquidity. Consequently, investors require higher expected returns, which makes asset prices fall if the rise in illiquidity does not have an appreciable positive effect on assets' cashflow. This generates a negative relationship between illiquidity shocks and asset realized returns, which is documented for stocks by Amihud (2002), for bonds by deJong and Driessen (2004), and is employed by Acharya and Pedersen (2005) in analyzing the effect of liquidity risk on stock expected return. However, these papers examine the *unconditional* effect of liquidity risk, that is, averaged over time. In particular, this body of research has by and large not yet examined the casual observation that the impact of liquidity shocks on asset prices is highly *conditional*, in particular, significantly stronger in "bad" economic times. Acharya and Pedersen (2005) note that significant illiquidity episodes in the stock market were preceded by significant macroeconomic or market-wide shocks during the period 1964-1999, [1] and Watanabe and Watanabe (2008) suggest a regime-switching pattern of response of stock returns to liquidity, but they do not relate it to macroeconomic conditions.

This paper shows that the response of corporate bond prices to liquidity shocks varies over time in a systematic way, switching between two regimes which we call "normal" and "stress." Liquidity shocks are measured for both stocks and treasury bonds, and the times of stress turn out to be periods when the effects of liquidity shocks on corporate bond prices differ greatly from these effects in the normal regime. We find that the periods of stress are associated with times of adverse macroeconomic conditions, such as recessed economic activity, and adverse financial market conditions. Notably, the relationship between bond returns and liquidity shocks in distress differ greatly for investment grade and non-investment-grade ("junk") bonds. While junk bond returns respond more negatively to illiquidity shocks in stress, investment-grade bond returns respond more positively. This time-varying or conditional pattern of liquidity risk of corporate bond returns is robust to controlling for other systematic risks that include interest rates and default risk. Important, it suggests a "flight to liquidity" phenomenon wherein investors faced with heightened macroeconomic stress prefer to hold more liquid assets such as investment grade bonds than less liquid ones such

[1] Over the period 1963 to 1999, they identify these shocks to be 5/1970 (Penn Central commercial paper crisis), 11/1973 (oil crisis), 10/1987 (stock market crash), 8/1990 (Iraqi invasion of Kuwait), 4-12/1997 (Asian crisis) and 610/1998 (Russian default, LTCM crisis).

as junk bonds.

In an out-of-sample estimation, our time-varying model enables us to explain the realized corporate bond returns during the 2008 financial crisis with substantial accuracy. We project the probability of being in the stress regime in each month of 2008 using the data until 2007 and show that the predicted return (using the projected probability and the return structure in the two regimes) explains well the realized returns on investment grade and junk bond during 2008. In regressions of realized returns on predicted returns we obtain $R^2$ that ranges between 47% and 64% (for junk and investment grade bonds, respectively), the coefficients on predicted return are close to one (and statistically indistinguishable from one). As shown in Figure 5, the predicted return does a reasonable job at explaining the highest stress months of March 2008 (Bear Stearns' collapse) and September to December 2008 (Lehman Brothers' collapse and the post-Lehman phase).

In another out-of-sample test we start with the second half of the sample and progressively estimate the best econometric fit using macroeconomic and financial-market variables that explain the model-implied probability of being in the stress regime until the previous month, and use it to predict the probability of being in the stress regime this month. The prediction has significant power with an accuracy of over 85%.

Formally, we estimate a two-regime switching model of betas of investment grade and junk bond returns (in excess of the 30-day Tbill rate) on two liquidity factors and two vectors of bond returns, which have been used in earlier studies. The two liquidity factors that we use measure innovations in market-wide liquidity on stocks and bonds: The average price-impact measure for stocks of Amihud (2002), as modified by Acharya and Pedersen (2005), and the average quoted bid-ask spread of on-the-run short-term treasury bonds, as in Goyenko (2006). The bond return coefficients on the innovations in these two liquidity factors measure liquidity risk as in Acharya and Pedersen (2005), constituting a liquidity beta that they label $\beta^3$. Our results on the changing beta series thus highlight the varying nature of bond liquidity risk.

The two vector of bond bond returns used are the return difference between Treasury thirty year long-term bonds and one month T-bill, and the return difference between all rated corporate bonds (equally weighted, with at least one year to maturity) and the average return of Treasury one year and thirty year long-term bonds. The betas of bond returns on these two return factors reflect the sensitivity of bond prices to changes in the slope of the yield curve and default risk.[2]

[2]We stress that by controlling for overall corporate bond market return, our analysis for picking up liquidity effects is rather conservative. It could very well be that the level of corporate bond return on

Our regime-switching estimation shows that the junk bond return betas on the two bond return factors (that reflect maturity and default risk) do not change appreciably between the two regimes, whereas the two liquidity betas, which are statistically insignificant in normal times, become highly negative and significant in the stress regime. A one standard deviation in either of the liquidity factors produces only one twentieth (or less) of a standard deviation shock in returns during normal times, whereas during time of stress, the effect is between one tenth to fifth of a standard deviation of bond returns. In other words, during stress times, the effect of liquidity risk on bond returns rises by a factor of two to four times compared to the normal times.

For investment grade bonds, the economic contribution of maturity risk rises in stress regime and that of default risk rises too (such that they become statistically indistinguishable from junk bonds in terms of both term and default risk betas). The more striking pattern is that in the stress regime, the investment grade returns respond more favorably to positive innovations in illiquidity, with the response being stronger to innovations in bond illiquidity.

We obtain that the model-implied probability of a given month being in the stress regime has economic content consistent with economic priors. In particular, it correlates with (lagged) macroeconomic variables that generally proxy for macroeconomic stress times: NBER recession, Stock and Watson index of leading economic indicators, the probability of being in a recession based on Hamilton's model, a dummy variable for negative market return, and the business conditions index of Arouba, Diebold and Scotti (2009). The probability of being in a stress regime also correlates with variable that reflect financial market stress: the yield spread between commercial paper and Treasury bills, the level of stock market illiquidity and that of treasury illiquidity, stock market volatility, and the interaction of stock market volatility and past year's growth in broker-dealer balance-sheets (as measured by Etula (2009)). The best econometric fit using these proxies explains about 43% of the time-series variation in model-implied probability of being in a stress regime.

One interpretation of these results is that during adverse conditions, investors respond to illiquidity shocks by switching from junk bonds to investment-grade bonds which are known to be more liquid (see Chen et al., 2007). Another alternative is that our liquidity risk variables proxy for heightened investor risk-aversion to extreme events or rare disasters (Rietz, 1988 and Barro, 2006) which induces an aversion to riskier assets such as junk bonds. Yet another explanation is the volatility feedback explanation of Campbell and Hentschel

average is itself responsive to stock and bond market liquidity. However, we treat the overall corporate bond market return as being entirely due to credit risk and look for liquidity effects at bond portfolio levels beyond the credit risk factor.

(1992) that increases in aggregate volatility necessitate a reduction in investor holdings of risky assets, which reduces their contemporaneous returns. To differentiate between these explanations, we study how (i) treasury bill spread relative to the Federal Funds rate and (ii) gold returns behave in the normal and the stress regimes (as identified in our analysis of the liquidity betas of corporate bond returns). While both treasury bills and gold are high "quality" assets in the sense of being relatively safe investments, treasury bills are highly liquid whereas gold is not. We find that both treasury bills and gold have higher returns on average during the stress regime, but the treasury bill return rises with an increase in liquidity risk whereas gold return falls. This is consistent with a flight-to-liquidity phenomenon rather than a flight-to-quality/safety one.

To summarize, corporate bond returns exhibit liquidity risk that has a significant conditional component during stress times for economy and markets. Our evidence shows that during deteriorated macroeconomic and financial market conditions, there is flight-to-liquidity whereby investors prefer more liquid assets, such as investment grade bonds, to less liquid ones, such as junk bonds. Indeed, in the stress times we identify in data for corporate bond returns, there is no clear pattern of an increase in the sensitivity of returns to traditional bond risk factors such as maturity and default risk.

Section 2 discusses related literature. Section 3 describes the data we employ. Sections 4 and 5 present results for our unconditional and conditional liquidity risk tests, respectively. Section 6 concludes.

# 2 Related literature

Like other assets, bond yields reflect their liquidity characteristics. Amihud and Mendelson (1991) show that short-term Treasury notes and Treasury bills with the same time to maturity have different yields due to differences in their liquidity (measured by the bid-ask spread and broker fees): Bills, which are issued frequently, are more liquid and then notes and consequently their yield is lower. Kamara (1994) finds that the notes-bills yield spread is an increasing function of liquidity risk, measured as a product of the volatility of yield and the ratio of the bills-to-notes turnover. Elton and Green (1998) find that differences in trading volume between Treasury securities explain differences in their yields. Boudoukh and Whitelaw (1993) find that the designated benchmark bonds in Japan, which are more liquid than similar bonds without such designation, have lower yield to maturity. And, Longstaff (2004) finds that higher yield on RefCorp government-agency bonds (issued by the

Resolution Funding Corporation) are higher than those on same-maturity Treasury bonds whose risk is the same, since the RefCorp bonds are less liquid.

The effect of liquidity of corporate bonds on their yields is analyzed by Chen, Lesmond and Wei (2007). They measure illiquidity, or the implicit bid-ask spread, by the imputed value change that is needed to induce a transaction in the bond, assuming that if that value change is smaller than transaction costs, a trade will not take place. They also use the quoted bid ask spread is a measure of illiquidity. They find that illiquidity is greater for non-investment grade bonds, and that after controlling for factors that affect yield, such as risk of default and maturity, the corporate yield spread over Treasury is an increasing function of illiquidity. The effect of illiquidity on bond yields is much larger for non investment grade bonds. Chen et al. also find in a time-series analysis that changes in illiquidity induce changes in yields in the same direction. Edwards, Harris and Piwowar (2007) and Goldstein, Hotchkiss and Sirri (2005) document corporate bond illiquidity using the TRACE data starting around 2002. Both papers employ a price-impact measure, and Goldstein et al. also employ bid-ask spread. Though their focus is the study of corporate bond transparency on its liquidity, their results suggest significant trading costs for corporate bonds.

Chacko (2005) imputes a corporate bond liquidity by assigning liquidity to a bond according to the turnover of the fund that holds it. The idea flows from Amihud and Mendelson (1986) that in equilibrium, liquid asset are held by more frequently-trading investors. Chacko then constructs a liquidity factor by sorting bonds into high- and low-liquidity portfolios and taking the return difference between them. The return on the high-minus-low liquidity portfolio is then used to price bonds. The results show that bond returns are increasing in the exposure to the bond risk factor, after controlling for other factors. Downing, Underwood and Xing (2005) study a similar issue, but their measure of bond liquidity is a proxy of corporate bond price impact similar to that of Amihud (2002). They find that long-term corporate bonds have greater beta with respect to the bond illiquidity factor and that liquidity shocks explain a sizable part of the time-series variation in bond returns. They further find that illiquidity risk is priced in a context of a linear APT model (with other factors: market, maturity and credit risk).

While these studies (and the more recent ones that we cite in concluding remarks) linking corporate bonds' liquidity to their returns or yields make a promising start, the data availability limits any significant time-series analysis, especially of conditional effects during times of economic stress, which is our primary focus in this paper. Hence, a number of papers including this paper have employed liquidity measures from treasury bonds (bid-ask spread or on-the-run to off-the-run spread) and stock markets (bid-ask spread or a price-impact measure). In particular, our analysis of corporate bond returns is over a long time-series from 1973 to 2008, allowing us to link liquidity effects to macroeconomic and financial market stress. Such robust analysis is not feasible if one relies on corporate bond market liquidity to measure liquidity risk as the only stress episode spanning TRACE data has been the crisis of 2007-09.

Longstaff, Mithal and Neis (2005) show that the basis between corporate bond spreads and credit default swap premia is explained by fluctuations in treasury liquidity. de Jong and Driessen (2005) follow Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) by estimating two liquidity *betas* of bond returns with respect to stock and bond liquidity shocks, using Amihud's (2002) *ILLIQ* for stock illiquidity and quoted bid-ask spreads on long-term U.S. Treasury bonds, as well as the beta on the S&P 500 index. They find that bonds with lower rating and longer maturities have more negative liquidity betas, implying that these bonds have higher illiquidity premium. The de Jong and Driessen study is the closest to our unconditional analysis (Table 2), but they have a much shorter time-series and do not isolate regime-switching behavior of liquidity betas as we do. Sangvinatsos (2009) studies the importance of corporate bonds in overall investor portfolio and documents that there exist flight-to-liquidity premia in investment grade bonds but not in high yield bonds.

Finally, the effect of bond liquidity transcends the bond market. Goyenko (2006) studies the cross-market effect of liquidity and finds that stock returns as well as Treasury bond returns are affected by both stock and bond liquidity shocks. Furthermore, the exposure of stocks to treasury bond liquidity appears priced in the cross-section of stock returns. Similarly, Fontaine and Garcia (2007) extract a common component of on-the-run U.S. Treasury bond premiums, similar to our measure of treasury bond liquidity, and show that when this "funding liquidity" factor predicts low risk premia for on-the-run and off-the-run bonds, it simultaneously predicts higher risk premia on LIBOR loans, swap contracts and corporate bonds.

# 3 Data

Our bond data are extracted from the Lehman Brothers Fixed Income Database distributed by Warga (1998) and supplemented by the Merrill Lynch corporate bond index database used by Schaefer and Strebulaev (2008). We follow closely the data extraction methodology outlined by Bharath and Shumway (2008) for the Warga (1998) database. The Warga

(1998) database contains monthly price, accrued interest, and return data on all corporate and government bonds from January 1971 - March 1997. We use the data from the 1973-1997 period when coverage becomes wide spread. This is the same database used by Elton et al.(2001) to explain the rate spread on corporate bonds. This database has also been used by Gebhardt et.al. (2005) in their study of cross section of bond returns. In addition, the database contains descriptive data on bonds, including coupons, ratings, and callability. A subset of the data in the Warga database is used in this study.

We employ several selection criteria. First, all bonds that were matrix priced rather than trader priced are eliminated from the sample[3]. Employing matrix prices might mean that all our analysis uncovers is the rule used to matrix-price bonds rather than the economic influences at work in the market. Eliminating matrix-priced bonds leaves us with a set of prices based on dealer quotes. This is the same type of data as that contained in the standard academic source of government bond data: the CRSP government bond file. Next, we eliminate all bonds with special features that would result in their being priced differently. This means we eliminate all bonds with options (e.g. callable bonds or bonds with a sinking fund), all corporate floating rate debt, bonds with an odd frequency of coupon payments, and inflation-indexed bonds. In addition, we eliminate all bonds not included in the Lehman Brothers bond indexes, because researchers in charge of the database at Lehman Brothers indicate that the care in preparing the data was much less for bonds not included in their indexes. This also results in eliminating data for all bonds with a maturity of less than one year.

This is supplemented by data from the monthly prices on corporate bonds that are included either in the Merrill Lynch Corporate Master index or the Merrill Lynch Corporate High Yield index used by Schaefer and Strebulaev (2008). These indexes include most rated US publicly issued corporate bonds. The data cover the period from December 1996 to December 2007. The same selection criteria used for the Lehman database were used with the Merrill database as well and thus, the bonds that constitute the two databases (during the overlapping period between the two databases (i.e.), December 1996 to March 1997) are nearly identical. It should be noted that in the Lehman database all bonds have missing data in August 1975 and December 1984. Most bond issues are rated by both S&P and Moody's and the ratings agree with each other.

[3]For actively traded bonds, dealers quote a price based on recent trades of the bond. Bonds for which a dealer did not supply a price have prices determined by a rule of thumb relating the characteristics of the bond to dealer-priced bonds. These rules of thumb tend to change very slowly over time and do not respond to changes in market conditions.

The monthly corporate bond return as of time $\tau + 1$, $r_{\tau+1}$ is computed as

$$r_{\tau+1} = \frac{P_{\tau+1} + AI_{\tau+1} + C_{\tau+1} - P_{\tau} - AI_{\tau}}{P_{\tau} + AI_{\tau}} \ , \tag{1}$$

where $P_{\tau}$ is the quoted price in month $\tau$; $AI_{\tau}$ is accrued interest, which is just the coupon payment scaled by the ratio of days since the last payment date to the days between last payment and next payment; and $C_{\tau+1}$ is the semiannual coupon payment (if any) in month $\tau + 1$. We value weight the monthly returns of all eligible bonds in each rating class by the total amount outstanding of each bond. This also helps us reduce significantly biases resulting from bad prices of particular bonds. Over the sample period 1973-2007, there were on average 2,234 bonds each month in the database. The minimum number of bonds in a month was 245 and the maximum was 9,286 over the entire period.

Table 1 Panel A reports the summary statistics of corporate bond returns by rating classes. AAA-rated bonds on average have earned 67.2 basis points (bps) over our sampe period, whereas bonds rated CCC and below earned 160.3 bps. As we move from AAA- to CCC-rated bonds, the variability of returns rises as well. For instance, CCC-rated bonds have a huge variability ranging from -905 bps to +1069.7 bps. For most of our analysis, we rely on groupings into investment-grade (BBB-rated and above) and junk (below BBB rated) bonds. This is for parsimony of estimated econometric systems. For these groupings, we find that investment grade bonds have on average earned 71.4 bps per month with a standard deviation of 146.3 bps, whereas junk bonds have earned 109.6 bps with a substantially higher standard deviation of 235.5 bps.

In benchmark specifications, following Fama and French (1993), we use two risk factors for corporate bonds. Common risk for corporate bonds arises from unexpected changes in the term structure of interest rates and from changes in default risk. Fama and French (1993) justify these choices by an ICAPM setting in which these two factors are hedging portfolios. Following the suggestions and results in Gebhardt et al (2005), we do not include the market factor because empirically they found that the market factor has almost no explanatory power for corporate bond returns in the presence of default and term risk factors.

Following Gebhardt et al (2005), we use Term, as the difference in the monthly long-term thirty year government bond return (from Ibbotson Associates) and one month T-bill returns (from the Center for Research in Security Prices, CRSP), as a proxy for the unexpected changes in the term structure, and Def, defined as the difference between the monthly return on a equally-weighted market portfolio of all corporate bonds with at least one year to maturity and the average of the monthly one year and long-term thirty year government bond return, as a proxy for default risk. We use an average of the one year and thirty year treasury return because corporate bonds in the sample used to construct the Def factor have maturities from one to thirty years. All of our results are qualitatively similar if we use the thirty year treasury return instead of the average, to construct the Def factor. We use equally weighted corporate bond returns to capture the extreme default outcomes each month.

We supplement these factors by two liquidity risk factors. The two liquidity risk factors we employ are the price-impact motivated measure for aggregate stock market of Amihud (2002), as calculated by Acharya and Pedersen (2005), and the equally weighted quoted bid-ask spread on on-the-run treasuries, as in Goyenko (2006).Acharya and Pedersen (2005) predict market illiquidity by running a regression of the *ILLIQ* measure of Amihud (2002) using a AR(2) specification. The residual of this regression is interpreted as the stock market illiquidity innovation (illiqinnov). The bond market illiquidty innovation series construction also uses a AR(2) specification residual in the aggregate treasury bond illiquidity series (bondilliqinnov) constructed by Goyenko (2006).

Panel B of Table 1 provides summary statistics on the bond market factor portfolios. The average risk premium for the default factor (Def) is 9.5 basis points per month, while the average risk premium for the term factor (Term) is 17.7 basis points per month. The default premium is quite small in relation to its standard deviation of 114 basis points. While this implies that we cannot reliably reject the null hypothesis of zero default premium, it was still found to be a factor explaining the cross section of bond returns by Gebhardt et al (2005). Panel C of Table 1 shows the pairwise correlations between Term, Def and the two liquidity risk factors. Term and Def are highly correlated, whereas the two liquidity risk factors are less correlated with each other, and less so with Term and more so with Def, but the magnitudes are quite small. This helps with a clean interpretation of the liquidity risk effects we identify.

Figure 1 plots the investment grade and junk bond returns over time which appear to be more variable during early 80's, the early 90's recession, and late 90's. Figure 2 plots the time-series of Term and Def. Finally, Figure 3 plots the standardized bond and stock market illiquidity innovations. The measured innovations in market illiquidity are high during periods that were characterized by liquidity crisis, for instance oil shock of 1973, the 1979-1982 period of high interest rates, the stock market crash of 1987, the 1990 recession and the 1998 LTCM crisis.

# 4 Unconditional liquidity risk

The effect of unpredictable variations in liquidity on asset prices have been extensively studied in the literature. in this section, we first examine as a benchmark the the unconditional effect of liquidity factors on corporate bond returns divided into categories by ratings.

## 4.1 Methodology and results

First, we estimate the following time-series specification:

$$\begin{aligned} R_{j,t} &= \alpha_j + \beta_{j,T} \times Term + \beta_{j,D} \times Def \\ &+ \beta_{j,I} \times Illiqinnov + \beta_{j,BI} \times Bondilliqinnov + \epsilon_{j,t} \ , \end{aligned} \tag{2}$$

for $R_{j,t}$ being the value-weighted return on corporate bonds of rating class $j$ in excess of the 30-day Tbill rate $j \in \{\text{AAA, ..., CCC \& Below, Unrated}\}$. Note that this specification resembles the Fama and French (1993) model to explain corporate bond returns, but we have augmented it with the two liquidity risk factors.

Table 2 Panel A presents the coefficient estimates. For all ratings, the loadings on Term and Def is positive. The Term factor loading is statistically significant for all rating classes. The Term loadings seem higher overall for ratings of BBB and above compared to those for BB and below, likely due to the longer maturity on average of higher-rated corporate bonds. The Def loadings are monotonically increasing down the ratings (except for the CCC group), consistent with worsening credit quality.

Of primary interest to this paper, the liquidity risk loadings are negative for all ratings below BBB and for both measures of liquidity risks. This implies that when stock-market and treasury illiquidity rises, junk bond returns tend to fall. In contrast, the stock and bond liquidity risk loadings are generally positive for all ratings above BBB. This effect is statistically significant for stock liquidity risks for BBB and above ratings while in the case of bond liquidity risk it is significant for AAA. For BB down to CCC and below, both liquidity risk betas are significant, whereas for Unrated bonds, neither illiquidity beta is significant (perhaps due to noisier data and infrequent trading). The most notable feature of the liquidity risk betas is that their magnitude is substantially higher for bonds rated BB and below compared to bonds rated above, usually by factors between four to ten. Overall, the coefficients on liquidity risks are also monotonically declining from positive to negative values as we move from AAA down to CCC bonds. Finally, the explanatory power of these models is reasonable for BBB and above (adjusted R-squared between 76% and 83%), but deteriorates substantially for BB and below (adjusted R-squared between 10% and 51%).[4]

Table 2 Panel B reports the economic magnitudes of the different factor loadings. In particular, it reports for each factor loading and each rating class, how many standard deviation in returns arises from a standard deviation shock to the factor. The calculations employ the summary statistics reported in Table 1. For BBB and above, the liquidity risks are not too significant in an unconditional sense: a one standard deviation shock to liquidity risks produces a meagre 1% to 8% of standard deviation in returns for these rating classes. For BBB and above, the economic magnitude of Term and Def effects is far more significant than that of liquidity risks, especially of Def. For BB and below, however, the economic magnitude of Term is slightly smaller. While we expect Term to have a stronger effect on higher-rated bonds as they have longer maturity compared to lower-rated bonds, the comparable economic magnitude of the effect of Def for higher-rated and lower-rated bonds is surprising.

The economic magnitude of the two liquidity risks is higher for BB and below, with one standard deviation shock to stock-market illiquidity producing between 12% to 34% of standard deviation in bond returns, the corresponding range for treasury illiquidity being 18% to 23%. One point to note here is that while the maximum shocks to Term, Def and stock-market illiquidity innovations are of the order of three standard deviations, the maximum shock to treasury-market illiquidity innovation is around five standard deviations. Thus, the realized economic impact of the latter innovation may be larger than Panel B suggests.

To summarize, Table 2 makes it clear that there is unconditional liquidity risk in corporate bond returns, but that it is substantially higher for junk bonds than for investment grade bonds, and importantly, they appear in fact to be intrinsically of different signs.

# 5 Conditional liquidity risk

As discussed in introductory remarks, most of the current academic literature has focused on unconditional liquidity risk as we also analyzed thus far. However, as noted by Acharya and

[4]It is worth mentioning that these results match those of de Jong and Driessen (2005), but there are some differences. In our Table 2, Panel A, $\beta_i$ and $\beta_{bi}$ are generally increasing in bond rating, whereas in de Jong and Driessen (Tables 4 and 5), $\beta_i$ is practically flat in rating, increasing only for BB and B and CCC ratings. In contrast, their $\beta_{bi}$ is increasing in rating. Note that they include S&P return on the right hand side whose beta is increasing monotonically in rating, while we do not, and instead include Term and Def, following much of the corporate bond literature following Fama and French (1993).

Pedersen (2005), stock market liquidity risk is the highest during episodes of high market return and high levels of illliquidity. These results suggest that while liquidity risk matters in an overall sense, it matters especially so, during episodes of illiquidity. Indeed, from an economic perspective, there are sound reasons to believe that the effect of liquidity risk is episodically high but muted in many periods. This could be because investor aversion to risk in general or to liquidity risk in particular may exhibit time-variation. Of greater relevance to corporate bonds, financial institutions are usually the marginal price-setters in these markets. Such institutions may be far away from their funding or capital constraints during normal times but when hit by adverse shocks to asset values or funding liquidity, e.g., during recessions or financial crises, they may reflect an aversion to holding corporate bonds in lieu of treasuries.[5] Such aversion would be particularly strong for worse rated bonds since they are not only riskier but also more illiquid. The case for conditionality in liquidity risk is thus strong apriori and we investigate it next.

## 5.1 Regime-switching model of bond betas

We perform a regime-switching analysis of corporate bond betas on various risk factors, separately for investment grade and junk bonds. In essence, we let the data tell us whether there is a set of times when betas are substantially stronger than other times. The apparent tendency of many economic variables such as GDP growth to behave quite differently during economic downturns has been studied by Hamilton (1989) using this method. This differential behavior is a prevalent feature of financial data as well and the regime switching approach has been used to examine how they could be detected in asset prices, as in Ang and Bekaert (2002). Watanabe and Watanabe (2007), using a similar methodology find evidence supportive of there being a regime switch in the nature of liquidity risk of stock returns.

### 5.1.1 Methodology

We estimate a Markov regime-switching model for corporate bond betas as follows where we allow alpha and all betas of bond returns of a given type (investment grade or junk) to be potentially different between two regimes. Note that we collapse returns of all bonds that are in investment grade or junk category to a single time-series of bond returns for that grade using a value weighted average.

[5] For theoretical motivation of the effects of these kinds of asset, volatility or funding shocks and the induced de-leveraging and market liquidity effects, see Gromb and Vayanos (2002), Acharya and Viswanathan (2007), and Brunnermeier and Pedersen (2009).

Investment grade bond excess returns (over the 30 day T-Bill return) in Regime $k$ ($s_t = k$) for $k \in \{1, 2\}$, are assumed to be generated by the process:

$$\begin{aligned} R_{IG,t} &= \alpha^k_{IG} + \beta^k_{IG,T} \times Term_t + \beta^k_{IG,D} \times Def_t \\ &+ \beta^k_{IG,I} \times Illiqinnov_t + \beta^k_{IG,BI} \times Bondilliqinnov_t + \epsilon^k_{IG,t}. \end{aligned} \tag{3}$$

The state variable $s_t$ determines whether it is regime 1 or regime 2 and the Markov switching probability for state transition is specified as:

$$P(s_t = 1 \mid s_{t-1} = 1) = p \text{ , and} \tag{4}$$

$$P(s_t = 2 \mid s_{t-1} = 2) = q \text{ .} \tag{5}$$

Similarly, junk grade bond excess returns (over the 30 day T-Bill return) in Regime $k$ ($s_t = k$) for $k \in \{1, 2\}$, are assumed to be generated by the process:

$$\begin{aligned} R_{Junk,t} &= \alpha^k_{Junk} + \beta^k_{Junk,T} \times Term_t + \beta^k_{Junk,D} \times Def_t \\ &+ \beta^k_{Junk,I} \times Illiqinnov_t + \beta^k_{Junk,BI} \times Bondilliqinnov_t + \epsilon^k_{Junk,t}. \end{aligned} \tag{6}$$

The Regime Dependent Variance-Covariance Matrix is specified as ($s_t$ = 1,2):

$$\Omega_{s_t} = \begin{pmatrix} \sigma^2_{IG,s_t} & \rho_{s_t}\ \sigma_{IG,s_t}\ \sigma_{Junk,s_t} \\ \rho_{s_t}\ \sigma_{IG,s_t}\ \sigma_{Junk,s_t} & \sigma^2_{Junk,s_t} \end{pmatrix}$$

This flexible covariance structure is intended to capture the notion that variance of both the IG and Junk returns as well as the correlation between the two can be different across the two regimes. The model is estimated using maximum likelihood estimation. Since the estimation procedure is standard (Hamilton, 1994), we do not provide details here but only the results. We test for linear hypothesis about the coefficients $H_0 : L\beta = c$ where L is a matrix of coefficients for the hypotheses and c is a vector of constants. The Wald chi-squared statistic for testing $H_0$ is computed as $\chi^2_W = (L\hat{\beta} - c)'[L\hat{V}(\hat{\beta})L']^{-1}(L\hat{\beta} - c)$. Under $H_0$, $\chi^2_W$ has an asymptotic chi-squared distribution with r degrees of freedom where r is the rank of L and V the variance covariance matrix of the coefficients. Two points are in order before we proceed. One, the probabilities of state transition are assumed to be constant rather than varying with some exogenous condition. In this sense, the conditionality of this model arises purely from the regime switch rather than the likelihood of the regime switch being based on some economic variable. We will however relate the estimated probability of being in regimes to macroeconomic and financial market variables. Second, the model also allows for residuals to be heteroscedastic between the two regimes.

### 5.1.2 Results

The results in Table 3 for the regime switch in IG and junk bond betas are striking. There are two clear regimes and importantly these are primarily regimes in liquidity betas for junk bonds. Regime 1 is characterized by relatively low and positive (negative) liquidity betas of investment grade (junk) bond returns none of which are statistically significant except for the stock illiquidity beta for IG bonds, whereas Regime 2 is characterized by much more positive (negative) liquidity betas which are statistically significant for investment grade (junk) bond returns. The Term and Def betas of investment grade bonds are statistically different across the regimes, but in terms of economic magnitude, the differences are smaller than those for liquidity betas. This is also the case for junk bonds. In other words, the behavior of corporate bond returns does not exhibit substantial variation in risk exposure to interest rate risk and default risk over our sample period across regimes. Tests of difference in liquidity betas between the two regimes are strongly significant for the treasury bond illiquidity factor, and also for both liquidity factors taken together, but what is remarkable is the relative magnitude. For instance, the stock-market liquidity beta in Regime 2 is fifteen times higher for junk bonds than that during Regime 1, and treasury liquidity beta is also about six times higher. Going forward, we call Regime 1 and Regime 2 as "normal" and "stress" regimes, respectively.

Collectively these results seem to indicate that IG bonds returns are more sensitive to the Def and Term risks across both regimes and liquidity betas are significant in the stress regime. The Junk bonds returns seem to be driven by the liquidity risks (in addition to the Term and Def risks), especially in the stress regime . Within the same regime, with the exception of the Term risk, junk bond betas are consistently higher for the Def and the two liquidity risks in comparison to the IG betas. The stress regime is also characterized by high volatility of bond returns for both IG and Junk grade bonds. The volatility of returns in the stress regime compared to the normal regime is more than twice as high for the IG bonds and about thrice as high for the Junk grade bonds.

How economically significant is this conditional liquidity risk of junk rated bonds? Table 4 reports how much of a standard deviation in returns is associated with a standard deviation shock to a risk factor, where both standard deviations are calculated separately for normal time and stress time and the corresponding normal time and stress time betas from Table 3 employed in the calculation. While Term and Def effects on junk bond returns decrease in the stress regime (percentage wise), the liquidity effects increase. Even though the effect of Term and Def is always greater than the liquidity risk factors in an absolute sense for junk bond returns, in normal times as well as in stress times, the stress times are coincident with a significant rise in the explanatory power of liquidity risk. In particular, a one standard deviation shock in stock-market and treasury liquidity is associated by between one-fifth to one-fourth of a standard deviation shock in junk bond returns in stress times, and this is about three to ten times as large as their effect in normal times. Based on the standard deviation of returns in stress times, this effect is estimated to be between 10 to 50 basis points per month (or 1.2 percent to 6 percent per year), which is substantial. Thus, Table 4 shows that the conditional liquidity risk effect in the stress regime can be quite magnified relative to their effects in the normal regime.

### 5.1.3 Stress regime and macroeconomic factors

In Figure 4, we plot the model-implied probability of being in the stress regime. The stress regime picks up most data points in 70's (picking up the oil-price shock of mid 70's and the high interest-rate regime of late 70's), early 80's (again, during the high interest-rate environment) and the financial market stress and the ensuring recession during the period 1998-2003. The regime-switching model also appears to pick up stress in 1989 leading up to the NBER recession of 1990 and 1991, but does not identify mid 90's. However, the Russian default and LTCM episode of 1998 are identified as being in the stress regime. The collapse of the internet bubble and its aftermath in March 2000 is also identified as stress regime. Finally, the probability of being in stress regime rises starting 2007 but not as dramatically.

In order to understand more formally what times constitute stress periods we consider one-month (or more) lagged value of both economy wide and financial market factors. We identify recessions by various available methodologies in the literature and capture market conditions by the stock market return and volatility as well as the level of stock and treasury market illiqudity. Specifically, as for Table 5 (even numbered estimations), we first convert the model-implied probability of being in stress regime into a binary variable which is set to one if the probability is higher than 70% (which gives us about 25% of data as being in stress regime), and zero otherwise. We relate this stress dummy using a logit model to dummy variables corresponding to five macroeconomic variables whose year-month values are shown in Appendix I. The odd numbered specifications in Table 5 employ the probability of being in the stress regime as a continuous variable in a OLS estimation.

The five macroeconomic variables are:

(i) NBER recession dates.

(ii) Mkt return (negative) which is a dummy in a given month if there have been three consecutive months of negative market return including the given month, where market return is measured as the CRSP Value weighted return with dividends.

(iii) The Business Conditions index: The Aruoba-Diebold-Scotti business conditions index (2009) is designed to track real business conditions at high frequency. The average value of the ADS index is zero. Progressively bigger positive values indicate progressively better-than-average conditions, whereas progressively more negative values indicate progressively worse-than-average conditions.

(iv) Prob(Recession) - Hamilton, a dummy variable if the probability of recession estimated from a Hamilton (1989) model on US GNP growth rates is greater than 70 percent (see Appendix II for its construction, also employing a regime-switching model).

(v) The Chicago Fed's CFNAI index (a follow up measure of the Stock and Watson (1989, 2002) recession index) with a bigger number indicating better business conditions.

In addition, we include as financial market variables

(vi) Paper bill spread, which is the the difference between the yield on the 3-month non-finnancial commercial paper rate and the 3-month treasury bill secondary market rate.

(vii) De-trended level of stock market illiquidity (that is, de-trended *ILLIQ*, same as the series we use before constructing the stock market illiquidity innovations).

(viii) De-trended level of treasury market illiquidity (that is, de-trended on-the-run spreads, same as the series we use for constructing the bond market illiquidity innovations).

(ix) Growth in balance-sheet of broker-dealers (the *EE measure*), as a measure of past risk appetite of financial intermediaries (as motivated by Adrian and Shin, 2008, and employed by Etula, 2009). We use the growth in intermediaries' (aggregate Broker-Dealer) assets relative to household asset growth as a measure of aggregate speculators' ease of access to capital. This data is constructed from the U.S. Flow of Funds data which is available only at quarterly frequency for the full sample period. In our prediction exercise, we use the growth rates based on past one year's data.

(x) Change in Equity market volatility (innovations), defined as log of the the square root of the sum of the squared returns on the CRSP value weighted index with dividends, computed for each month using daily returns in that month divided by the same measure computed in the previous month.

(xi) Interaction of change in equity market volatility with the EE measure.

Table 5 shows the relationship between stress variable based on the regime-switching model and these macroeconomic and financial market measures of stress times. Both the OLS regression results (odd numbered specifications) and the logit estimates (even numbered specifications) provide similar evidence. All individual correlations with the individual macroeconomic series we use (variables i through v above) have the expected sign, and are statistically significant. This is by and large also true of the financial market variables. Interestingly, the level of treasury illiquidity is negatively related to the stress regime, again consistent with a flight to liquidity effect. The stress regime is also related to higher stock market volatility innovations. While past risk appetite of financial intermediaries (the EE measure) by itself lowers the likelihood of being in the stress regime, past risk appetite when coincident with a rise in stock market volatility, in fact increases the likelihood of being in the stress regime. This is consistent with financial intermediaries providing liquidity to corporate bond markets when their balance-sheets are growing, but withdrawing this liquidity (de-leveraging) when they face times with high increases in volatility.

In general, the robust conclusion that emerges is that regime 2, the stress regime, is associated with worsening macro economic and stock market returns. When employed in isolation, explanatory variables have R-squared's of the order of 10% to 20%. When all variables are used to employ the model-implied probability of being in the stress regime of liquidity risk of corporate bond returns, the NBER recession, business conditions index and equity volatility are important predictors. Though the R-squared is modest at 43%, this is typical of such associations between variables that describe the relatively rare stress periods of the economy. Figure 4, in fact, illustrated the positive even if imperfect relationship between the model-implied probability of stress and NBER recession months. This provides a measure of confidence that our regime-switching results on liquidity betas of junk bonds (Table 3) have an underlying economic foundation. And given this foundation, our priors are that the regime-switching model of Table 3 is not just an in-sample statistical description of the returns data, but in fact would have power to predict time-variation in returns even in out-of-sample analysis. We conduct such analysis next.

## 5.2 Out of Sample Tests

This section provides the estimates of an out-of-sample test that predicts the stress regime (Regime 2) of the Markov regime switching model of Table 3 using economic variables identified in Table 5. First we fit a model similar to model 16 of Table 5, using all the economic indicators to predict the stress regime employing only the data for the first half of our sample period, from January 1973 to December 1989. We exclude the NBER recession dummy in this exercise as a covariate due to the hindsight involved in dating recession periods. Using this model and economic covariates we predict the probability of being in the stress regime for the second half of the sample period, which is January 1990 to December 2007. This variable is called Predicted Prob(Regime 2). In particular, we predict the stress regime for the month of January 1990 employing the data on economic and financial covariates till December 1989, to estimate the equivalent of model 16 of Table 5; then for February 1990, we use all data till January 1990 to re-estimate this model. That is, we roll forward every month, using the data available till the previous month to develop a predictive model for the stress regime until the current month and then use the model to predict stress regime for the current month, and repeat this process till the end of the sample. We then present a logistic regression using this variable as the independent variable to explain the likelihood of being in the stress regime in the second half of the sample.

Results in Table 6 indicate that the predicted probability of being in the stress regime using the economic conditions as covariates is statistically significant in predicting the actual stress regimes in the second half of the sample period with a pseudo R-squared of 27%. The diagnostic performance of the model is the accuracy of the model to discriminate stress (regime 2) months from normal months is evaluated using a Receiver Operating Characteristic (ROC) curve analysis.

The ROC curve analysis works as follows. For every possible cut-off point or criterion value selected in the logit model to discriminate between the two regimes, there will be some cases with the stress months correctly classified as positive (TP = True Positive fraction), but some cases with the stress will be classified negative (FN = False Negative fraction). On the other hand, some normal months will be correctly classified as non stress months or negative (TN = True Negative fraction), but some normal months will be classified as stress months or positive (FP = False Positive fraction). In a Receiver Operating Characteristic (ROC) curve the true positive rate (Sensitivity) is plotted as a function of the false positive rate (100-Specificity) for different cut-off points. Each point on the ROC plot represents a sensitivity/specificity pair corresponding to a particular decision threshold. A completely random guess would give a point along a diagonal line (the so-called line of no-discrimination) from the left bottom to the top right corners. A test with perfect discrimination (no overlap in the two regimes) has a ROC plot that passes through the upper left corner (100% sensitivity, 100% specificity). Therefore the closer the ROC plot is to the upper left corner, the higher the overall accuracy of the test.

We therefore, present a figure that displays the ROC curve to assess the accuracy of this logit model to predict regime 2, the stress regime. In the Y-axis we plot the true positive rate (sensitivity), i.e. the proportion of actual stress regime months correctly classified by the model. In the X-axis we plot the false positive rate (1-specificity), the proportion of normal regime months, incorrectly classified as stress regime months by the model. Points above the diagonal (random guess) indicate good classification results. The area under the curve measures the accuracy of the model. The model has an impressive accuracy rate of about 86%. In other words, using lagged economic conditions as indicators in real time, the model is able to predict the stress regimes in corporate bond returns with a high level of accuracy. This provides an economic interpretation of the stress regime with heightened liquidity risk as one associated with worsening economic and financial market conditions.

## 5.3 Out of Sample Predictions during the financial crisis of 2008

This section provides the estimates of an out-of-sample test that predicts actual bond returns during the financial crisis of 2008. Once again, using the macroeconomic and financial market variables, we predict the probability of a given month of 2008 being in the stress regime (Regime 2). As before, we use specification (16) of Table 5. Then, we obtain the predicted bond returns for each month of 2008 by weighing the the respective regime probabilities with the predicted bond returns in each regime in the year 2008 (using the coefficients estimated on Term, Def and liquidity risk factors in each regime shown in Table 3 and the realized values of Term, Def and liquidity risk factors).

In Table 7 Panel A we document the realized (excess) bond returns in each month of 2008 for investment grade and junk bonds. The data reveal interesting patterns. In the first half of 2008, investment grade and junk bond returns appear to rise and fall more or less coincidentally; as expected, the response of junk bond returns is greater in either direction. However, in the second half of 2008, this pattern is not as robust and is in fact reversed. While junk bond returns keep falling from July through October, the investment grade returns fall only in August and September, and in fact show a sharp reversal in October. To be precise, in July and October, investment grade and junk bond returns are respectively $(0.2, 321.6)$ bps and $(-103.8, -744.3)$ bps, whereas in August, September, November and December they appear to move more coincidentally. Note though that the fall in junk bond returns in the cataclysmic month of September (Lehman Brothers and A.I.G. problems bringing the global financial sector to a standstill) is about six times as large as that in investment grade bond returns.

Is our prediction based on the regime-switching models of Table 3 and Table 5 capture these patterns? In Figure 5, we plot the realized bond returns against the predicted bond returns. Each number on the graph corresponds to the particular month in 2008. Two types of diagnostics are computed: RMSE (the root mean squared error) assuming a 100% fit between the predicted and the realized returns, and the RMSE after fitting a regression line with a constant between the predicted and the realized returns.

The regression of the predicted regime-switching model of returns against the realized returns has a reasonable fit of 47% for the junk grade bonds and 64% for the investment grade bonds. Further the coefficient on the predicted return is statistically indistinguishable from one for both bond grades and the constant is no different from zero in these regressions. The RMSE of the regression is very close to the RMSE of the 100% fit suggesting that the regression line does a good of explaining the actual returns with the predicted returns. It can also be seen that the model is able to predict bond returns reasonably also during the crisis months of Bear Stearns' collapse (March), Lehman Brothers' Bankruptcy (September) and the post-Lehman collapse months (October through December).

Overall, we conclude that the regime-switching model provides a good description of bond returns during the financial crisis of 2008.

## 5.4 Flight to liquidity or flight to quality?

One interpretation of our overall results is that during adverse conditions, investors respond to illiquidity shocks by switching from junk bonds to investment-grade bonds which are known to be more liquid (see Chen et al., 2007).[6] Another alternative is that our liquidity risk variables proxy for heightened investor risk-aversion to extreme events or rare disasters (Rietz, 1988 and Barro, 2006). Such events are argued to affect consumption in a highly significant way or argued to be not well understood, so that an increase in their likelihood induces an aversion to riskier assets such as junk bonds. Similar to this second alternative is the volatility feedback explanation of Campbell and Hentschel (1992) that increases in aggregate volatility necessitate a reduction in investor holdings of risky assets, which in

[6]Chen, Lesmond and Wei (2007) show that for medium-maturity (7 to 15 year) bonds in their sample over the period , investment grade bonds have bid-ask spread of about 40 bps on average whereas junk bonds have a spread of over 100 bps on average: at the two extremes, AAA-rated bonds have bid-ask spread of 50 bps where bonds rated CCC and below have a spread of over 180 bps. Even more strikingly, the frequency of zero-return days, another commonly employed proxy of illiquidity and stale quotes, is of the order of 6-10 percent for investment grade bonds and 20-40 percent for junk bonds.

general equilibrium, implies a reduction in their contemporaneous returns. It is important to tease, to the extent possible, which of these explanations – flight-to-liquidity or flight-to-quality/safety – is at work.

To differentiate between the two explanations, we study how (negative of) the treasury bill spread relative to the overnight effective Federal Funds rate and gold returns (measured as the log change of the monthly price of gold obtained from the World Gold Council) behave in the normal and the stress regimes. While both treasury bills and gold are high "quality" assets in the sense of being relatively safe investments, treasury bills are highly liquid whereas gold is relatively not as liquid as T-bills.

Table 8 shows the liquidity beta estimates of treasury bill and gold returns, allowed to vary based on the probability of being in the stress regime (estimated in regime-switching model of Table 3).[7] We find that both treasury bills and gold have higher returns on average during the stress regime, but the treasury bill return rises with an increase in liquidity risk whereas gold return falls. In other words, treasury bills behave in a manner that is consistent with the behavior of investment grade bonds while gold does so with the junk bond returns. This is consistent with a flight-to-liquidity phenomenon rather than a flight-to-quality one.

# 6 Conclusion

What are the implications of conditional liquidity risk we documented in this paper for corporate bond returns? Put simply, our evidence implies that during stress periods, liquidity risk is a significant factor in affecting bond prices, especially of low-rated bonds. Ignoring investors' flight to liquidity and adhering to normal-time models is thus prone to significant errors for researchers and investors in corporate bonds. For instance, the risk management of corporate bond portfolios should consider not only its liquidity risk, but also the risk that this risk will change. To the extent that investment grade bonds benefit during stress periods whereas junk bonds get hurt, our results imply some diversification of this risk in broad corporate bond portfolios.

We acknowledge that a relevant factor for corporate bond returns is also the liquidity specific to corporate bond market, since this liquidity may not necessarily be spanned by treasury bond and stock market illiquidity. First, the corporate bond market trading tends to be highly institutional in nature and shocks relevant for these institutions may need to be identified. Chacko (2005) and Chacko, Mahanti, Mallik and Subrahmanyam (2005) employ

[7] Note that we do not employ Term and Def as risk factors in explaining treasury bill returns.

a liquidity measure based on turnover of portfolios containing corporate bonds and find that a return factor based on high and low liquidity bonds explains the cross-section of bond returns. Acharya, Schaefer and Zhang (2007)'s study of the excess co-movement in credit default swaps around the General Motors (GM) and Ford downgrade of May 2005 shows that the co-movement was linked to the risk faced by corporate-bond market-makers when there were sudden liquidations of GM and Ford bonds. Further investigation along these lines seems to be a fruitful avenue for research.

Second, some of the recent studies such as Edwards, Harris and Piwowar (2007), Goldstein, Hotchkiss and Sirri (2005), Dick-Nielsen, Feldhutter and Lando (2008), Bushman, Le and Vasvari (2009), and Friewald, Jankowitsch and Subrahmanyam (2009) use newly available daily trading data on corporate bonds from TRACE platform in the United States. The last three of these papers also show that liquidity worsened substantially for corporate bonds from the onset of the crisis and that this contributed to an enhanced response of bond spreads or returns to liquidity. These effects are entirely consistent with the conditional liquidity effects we uncovered for corporate bonds over the period 1973 to 2008, even though due to data limitations we did not explicitly employ any corporate bond liquidity measure.

Finally, recent work (Panyanukul, 2009) has also found liquidity risk to be a priced factor in explaining sovereign bond returns, especially during the period 2007 to 2009. We conjecture that there is a strong conditional component to liquidity effects therein too, whereby during times of macroeconomic and financial market stress, better-rated sovereign bonds appreciate in value whereas the worse-rated ones decline.

# Appendix I

**Recession dates (year-month) based on macroeconomic data.**

NBER Business Cycles: The economic expansions and recessions are determined by the NBER business-cycle dates. The expansions (recessions) begin at the peak (trough) of the cycles and end at the trough (peak). The following Table provides periods and durations (in months) of each business-cycle phase during our sample period, January 1973 to December 2003. The business-cycle dates are available from the NBER website: www.nber.org/cycles.html. The dates are 12/73-03/75;02/80-07/80;08/81-11/82;08/90-03/91; 03/01-11/01; and 12/07;

Prob(Recession) - Hamilton: Following Hamilton (1989), we estimate the growth in GNP as a regime switching model (details in Appendix II). Hamilton (1989) interprets the probability of being in regime 1 as the recession regime. We use a cut off of the probability of being in regime 1 greater than 70% to create this dummy variable. Quarters that are classified as recession in this approach include: 1974-2 to 1975-1; 1980-2,3; 1981-2; 1981-4 to 1982-4; 1986-2; 1990-3 to 1991-4; 1993-2,3; 1995-2,3; 1998-2; 2000-3 to 2003-1; 2006-3 to 2007-1;

Mkt Return (negative): We code a month that is the third consecutive month in which the CRSP value weighted market return with dividends is negative as a one and zero otherwise. Months classified under this classification using our sample period include: 03/73 to 06/73; 05/74 to 09/74; 09/75; 03/77; 08/81 to 09/81; 02/82-03/82; 07/82 ; 02/84; 11/87; 08/90 to 10/90; 09/99; 11/00; 08/01 - 09/01; 06/02-07/02; 12/02; 02/03; 07/06; and 09/07 to 12/07;

SW index : "The Chicago Fed National Activity Index (CFNAI) is a monthly index designed to better gauge overall economic activity and inflationary pressure. The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend. The CFNAI corresponds to the index of economic activity developed by James Stock of Harvard University and Mark Watson of Princeton University in an article, "Forecasting Inflation," published in the Journal of Monetary Economics in 1999. The idea behind their approach is that there is some factor common to all of the various inflation indicators, and it is this common factor, or index, that is useful for predicting inflation. Research has found that the CFNAI provides a useful gauge on current and future economic activity and inflation in the United States". (Reproduced from www.chicagofed.org). An index similar in spirit is also the business conditions index which is also used in the analysis. The (ADS) business conditions index is based on the framework developed in Aruoba, Diebold and Scotti (2009). The average value of the index is zero. Progressively bigger positive values indicate progressively better-than-average conditions, whereas progressively more negative values indicate progressively worse-than-average conditions.

# Appendix II

**Estimation of recession periods using Hamilton (1989)'s Markov Switching model.**

This Table reports the results of the following markov switching model for the quarterly growth rate in US GNP ($y_t$):

Regime 1 ($s_t = 1$): $y_t = \alpha_1 + u_t$, and
Regime 2 ($s_t = 2$): $y_t = \alpha_2 + u_t$, where
$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \rho_3 u_{t-3} + \rho_4 u_{t-4} + e_t, e_t \sim N(0, \sigma)$.

The Markov switching probability for state transition is given by:
$P(s_t = 1 \mid s_{t-1} = 1) = p$, and
$P(s_t = 2 \mid s_{t-1} = 2) = q$.

Following Stock and Watson's (2002) observation of a structural break in the GNP series in 1984, we estimate the model for two distinct time periods: 1952 (Quarter 2) to 1984 and from 1985 to 2008 (Quarter 3). We use these models to estimate the probability of being in regime 1 (interpreted by Hamilton (1989) as the recession regime) which is used in specifications of Table 7, Panel A and B.

| Period | 1952:2 to 1984:4 | | | 1985:1 to 2008:3 | | |
|---|---|---|---|---|---|---|
| Parameter | Value | Std.Error | t-Value | Value | Std.Error | t-Value |
| $\alpha_1$ | -0.3403 | 0.2441 | -1.39 | 0.8738 | 0.1880 | 4.65 |
| $\alpha_2$ | 1.1727 | 0.1423 | 8.24 | 1.5922 | 0.2223 | 7.16 |
| $\rho_1$ | 0.0108 | 0.0895 | 0.12 | -0.2506 | 0.0992 | -2.53 |
| $\rho_2$ | -0.0627 | 0.0811 | -0.77 | 0.1994 | 0.0822 | 2.43 |
| $\rho_3$ | -0.2462 | 0.0859 | -2.87 | -0.0532 | 0.0845 | -0.63 |
| $\rho_4$ | -0.2009 | 0.0867 | -2.32 | 0.0391 | 0.0802 | 0.49 |
| $\sigma$ | 0.7699 | 0.0608 | 12.66 | 0.3246 | 0.0321 | 10.12 |
| p | 0.9014 | | | 0.7502 | | |
| q | 0.7620 | | | 0.8578 | | |
| Log L | -181.4 | | | -56.44 | | |
| Observations | 131 | | | 95 | | |

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**Table 1 Panel A: Summary statistics on bond returns by credit rating classes.** This table reports in basis points the returns on corporate bonds by credit rating classes. IGRADE stands for bonds rated BBB and above. To be included in a credit rating class, the bond must be in the Lehman/Merrill databases with at least one year to maturity, with each bond's return value weighted by the amount outstanding in that month. Returns are calculated using quoted prices or trades and matrix prices are discarded. The sample is from January 1973 through December 2007.

| Credit Rating | N | Mean | Std.Dev | Median | Min | Max |
|---|---|---|---|---|---|---|
| AAA | 415 | 67.2 | 134.5 | 63.0 | -535.4 | 736.8 |
| AA | 409 | 72.6 | 146.0 | 71.3 | -414.7 | 772.3 |
| A | 415 | 72.1 | 152.5 | 73.8 | -466.4 | 667.5 |
| BBB | 413 | 73.5 | 152.0 | 77.5 | -500.2 | 745.7 |
| BB | 405 | 89.2 | 167.7 | 90.8 | -670.1 | 850.0 |
| B | 405 | 99.4 | 221.7 | 108.7 | -804.0 | 1069.7 |
| CCC & Below | 369 | 160.3 | 332.0 | 148.6 | -905.0 | 1069.7 |
| Not rated | 289 | 87.9 | 169.8 | 81.4 | -598.0 | 791.3 |
| IGRADE | 1652 | 71.4 | 146.3 | 71.4 | -535.4 | 772.3 |
| JUNK | 1468 | 109.6 | 235.5 | 102.3 | -905.0 | 1069.7 |

**Table 1 Panel B: Summary statistics on bond market factors.** This table documents the return on the four factor portfolios DEF, TERM, ILLIQINNOV and the BONDILLIQINNOV factor. The sample is from January 1973 through December 2007. We use the Lehman Brothers Fixed income database for the period January 1973 to December 1996 and supplement it with data from the Merrill Fixed Income Securities Database for the period January 1994 to December 2007. The default factor (DEF) is defined as the difference between the equally weighted return on all bonds in the database with at least one year to maturity and the return on the average of one year and thirty year long term government bond return series from CRSP. The term factor (TERM) is the difference between the thirty year long term government bond return and the one month T-bill return from the CRSP database. ILLIQINNOV is the innovation in stock market illiquidity as in Acharya and Pedersen (2005), and calculated as the residuals of an AR(2) process. BONDILLIQINNOV is the innovation in bond market illiquidity using short maturity on-the-run treasuries bid-ask spread as in Goyenko (2006), and calculated as the residuals of an AR(2) process.

| | N | Mean | Std.Dev | Median | Min | Max |
|---|---|---|---|---|---|---|
| TERM | 420 | 17.7 | 319.6 | 19.6 | -1055.5 | 1162.5 |
| DEF | 420 | 9.5 | 113.5 | 10.6 | -625.1 | 616.9 |
| ILLIQINNOV | 420 | 0.01305 | 0.18955 | -0.01090 | -0.61920 | 0.84578 |
| BONDILLIQINNOV | 420 | 0.00694 | 0.43048 | 0.03318 | -1.48166 | 2.12169 |

**Table 1 Panel C : Pairwise correlations of bond market factors.** This table reports the pairwise spearman correlations of the bond market factors for the period January 1973 to December 2007.

| | TERM | DEFAULT | ILLIQINNOV | BONDILLIQINNOV |
|---|---|---|---|---|
| TERM | 1 | | | |
| DEF | -0.529 | 1 | | |
| ILLIQINNOV | -0.005 | -0.180 | 1 | |
| BONDILLIQINNOV | -0.055 | -0.059 | 0.085 | 1 |

**Table 2 : Time series portfolio level factor regressions with bond market factors** This table reports time series regressions of the returns on ratings based bond portfolios (in excess of the 30 day T-Bill return) on the TERM and DEF factors ($\beta_t$ & $\beta_d$). The sample is from January 1973 through December 2007. We use the Lehman Brothers Fixed income database for the period January 1973 to December 1996 and supplement it with data from the Merrill Fixed Income Securities Database for the period January 1994 to December 2007. The default factor (DEF) is defined as the difference between the equally weighted return on all bonds in the database with at least one year to maturity and the return on the average of one year and thirty year long term government bond return series from CRSP. The term factor (TERM) is the difference between the long term government bond return and the one month T-bill return from the CRSP database. We report the regressions with the ILLIQINNOV, and BONDILLIQINNOV variables added ($\beta_i$ & $\beta_{bi}$). ILLIQINNOV is the innovation in stock market illiquidity as in Acharya and Pedersen (2005), and calculated as the residuals of an AR(2) process. BONDILLIQINNOV is the innovation in bond market illiquidity using short maturity on-the-run treasuries bid-ask spread as in Goyenko(2006), and calculated as the residuals of an AR(2) process. Panel A reports the regressions by credit rating classes.

Panel A

| | Coefficients | | | | | | t-Stat | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rating | $\alpha$ | $\beta_t$ | $\beta_d$ | $\beta_i$ | $\beta_{bi}$ | Adj-Rsq | $\alpha$ | $\beta_t$ | $\beta_d$ | $\beta_i$ | $\beta_{bi}$ | N |
| AAA | -0.51 | 0.42 | 0.76 | 53.70 | 14.38 | 0.76 | -0.16 | 35.84 | 22.69 | 3.12 | 1.93 | 415 |
| AA | 3.74 | 0.47 | 0.81 | 34.44 | 2.86 | 0.78 | 1.11 | 37.98 | 22.88 | 1.88 | 0.37 | 409 |
| A | 2.16 | 0.50 | 0.90 | 38.93 | -1.20 | 0.83 | 0.69 | 43.68 | 27.35 | 2.31 | -0.16 | 415 |
| BBB | 3.50 | 0.47 | 0.97 | 34.06 | -11.77 | 0.75 | 0.92 | 33.90 | 24.45 | 1.66 | -1.34 | 413 |
| BB | 21.58 | 0.37 | 0.96 | -83.98 | -56.92 | 0.51 | 3.61 | 17.15 | 15.47 | -2.59 | -4.14 | 405 |
| B | 34.36 | 0.34 | 0.97 | -166.29 | -70.50 | 0.30 | 3.66 | 9.98 | 9.87 | -3.25 | -3.25 | 405 |
| CCC & below | 99.51 | 0.20 | 0.87 | -238.58 | -67.09 | 0.10 | 5.96 | 3.26 | 5.14 | -2.65 | -1.80 | 369 |
| Unrated | 15.88 | 0.30 | 0.85 | 30.02 | -23.73 | 0.28 | 1.83 | 10.17 | 5.05 | 0.57 | -1.16 | 289 |

Panel B

| | Ratio to $\sigma_{returns}$ of | | | |
|---|---|---|---|---|
| Rating | $\sigma_t$ | $\sigma_d$ | $\sigma_i$ | $\sigma_{bi}$ |
| AAA | 100.08% | 129.03% | 7.57% | 4.60% |
| AA | 102.17% | 135.92% | 4.85% | 0.92% |
| A | 105.34% | 152.17% | 5.48% | 0.38% |
| BBB | 99.07% | 164.51% | 4.80% | 3.77% |
| BB | 71.17% | 162.44% | 11.83% | 18.21% |
| B | 49.27% | 163.42% | 23.43% | 22.56% |
| CCC & below | 18.81% | 147.45% | 33.61% | 21.47% |
| Unrated | 57.31% | 143.26% | 4.23% | 7.59% |

**Table 3: Estimation of a markov regime switching model**
This table provides the estimates of the following model.

Investment Grade Returns (in excess of the 30 day T-Bill return):

Regime 1: $r_{IG,t} = \alpha^1_{IG} + \beta^1_{IG,T} Term_t + \beta^1_{IG,D} Def_t + \beta^{ILLIQ}_{IG,1} Illiqinnov_t +$
$\beta^1_{IG,BI} Bondilliqinnov_t + \epsilon^1_{IG,t}$

Regime 2: $r_{IG,t} = \alpha^2_{IG} + \beta^2_{IG,T} Term_t + \beta^2_{IG,D} Def_t + \beta^{ILLIQ}_{IG,2} Illiqinnov_t +$
$\beta^2_{IG,BI} Bondilliqinnov_t + \epsilon^2_{IG,t}$

Junk Grade Returns (in excess of the 30 day T-Bill return):

Regime 1: $R_{Junk,t} = \alpha^1_{Junk} + \beta^1_{Junk,T} Term_t + \beta^1_{Junk,D} Def_t + \beta^1_{Junk,I} Illiqinnov_t +$
$\beta^1_{Junk,BI} Bondilliqinnov_t + \epsilon^1_{Junk,t}$

Regime 2: $R_{Junk,t} = \alpha^2_{Junk} + \beta^2_{Junk,T} Term_t + \beta^2_{Junk,D} Def_t + \beta^2_{Junk,I} Illiqinnov_t +$
$\beta^2_{Junk,BI} Bondilliqinnov_t + \epsilon^2_{Junk,t}$

Regime Dependent Variance-Covariance Matrix ($s_t$ = 1,2):

$$\Omega_{s_t} = \begin{pmatrix} \sigma^2_{IG,s_t} & \rho_{s_t}\ \sigma_{IG,s_t}\ \sigma_{Junk,s_t} \\ \rho_{s_t}\ \sigma_{IG,s_t}\ \sigma_{Junk,s_t} & \sigma^2_{Junk,s_t} \end{pmatrix}$$

Markov switching probability for state transition:

$P(s_t = 1 \mid s_{t-1} = 1) = p$
$P(s_t = 2 \mid s_{t-1} = 2) = q$

We test for linear hypothesis about the coefficients $H_0 : L\beta = c$ where L is a matrix of coefficients for the hypotheses and c is a vector of constants. The Wald chi-squared statistic for testing $H_0$ is computed as $\chi^2_W = (L\hat{\beta} - c)'[L\hat{V}(\hat{\beta})L']^{-1}(L\hat{\beta} - c)$. Under $H_0$, $\chi^2_W$ has an asymptotic chi-squared distribution with r degrees of freedom where r is the rank of L and V the variance covariance matrix of the coefficients.

| **Regime 1** | | | | | | |
|---|---|---|---|---|---|---|
| | Investment Grade | | Junk Grade | | Parameters | |
| | Coeff | t-stat | Coeff | t-stat | | |
| Constant | 1.83 | 1.09 | 30.20 | 5.14 | p | 0.95 |
| Term | 0.35 | 49.10 | 0.28 | 12.62 | q | 0.93 |
| Def | 0.37 | 11.94 | 1.11 | 9.59 | $\rho_{s_t=1}$ | 0.11 |
| Illiqinnov | 17.80 | 1.92 | -16.04 | -0.45 | $\rho_{s_t=2}$ | -0.38 |
| Bondilliqinnov | -1.39 | -0.30 | -11.77 | -0.76 | | |
| $\sigma_i$ | 23.52 | | 81.40 | | | |
| **Regime 2** | | | | | | |
| | Investment Grade | | Junk Grade | | | |
| | Coeff | t-stat | Coeff | t-stat | | |
| Constant | 4.04 | 0.90 | 33.46 | 2.19 | | |
| Term | 0.52 | 30.75 | 0.43 | 7.42 | | |
| Def | 0.97 | 26.87 | 1.00 | 8.41 | | |
| Illiqinnov | 47.15 | 2.29 | -247.61 | -4.27 | | |
| Bondilliqinnov | 22.39 | 2.55 | -62.33 | -2.08 | | |
| $\sigma_i$ | 53.37 | | 184.19 | | | |
| Wald tests for differences in coefficients between Regime 1 and Regime 2 | | | | | | |
| | Investment Grade | | Junk Grade | | | |
| | Chi-Sq | p-value | Chi-Sq | p-value | | |
| Term & Def | 10.53 | 0.01 | 4.99 | 0.08 | | |
| Liquidity | 1.42 | 0.49 | 21.17 | 0.00 | | |
| Term | 93.72 | 0.00 | 5.09 | 0.02 | | |
| Def | 168.84 | 0.00 | 0.39 | 0.53 | | |
| Illiqinnov | 1.70 | 0.19 | 15.92 | 0.00 | | |
| BondIlliqinnov | 5.69 | 0.02 | 2.29 | 0.1 | | |
| Wald tests for differences in coefficients between IG and Junk | | | | | | |
| | Regime 1 | | Regime 2 | | | |
| | Chi-Sq | p-value | Chi-Sq | p-value | | |
| Term & Def | 3.69 | 0.16 | 1.43 | 0.49 | | |
| Liquidity | 6.24 | 0.04 | 32.32 | 0.00 | | |
| Term | 9.58 | 0.00 | 2.12 | 0.15 | | |
| Def | 37.81 | 0.00 | 0.05 | 0.82 | | |
| Illiqinnov | 0.87 | 0.35 | 20.82 | 0.00 | | |
| BondIlliqinnov | 0.46 | 0.50 | 6.14 | 0.01 | | |
| Log Likelihood | -4675.94 | | | | | |
| Sample Period | 1973:01 - 2007:12 | | | | | |

**Table 4: Economic Significance of regime switching model estimates**. The sample is from January 1973 through December 2007. We use the Lehman Brothers Fixed income database for the period January 1973 to December 1996 and supplement it with data from the Merrill Lynch Fixed Income Securities Database for the period January 1994 to December 2007. The default factor (DEF) is defined as the difference between the equally weighted return on all bonds in the database with at least one year to maturity and the return on the average of one year and thirty year long term government bond return series from CRSP. The term factor (TERM) is the difference between the long term government bond return and the one month T-bill return from the CRSP database. ILLIQINNOV is the innovation in stock market illiquidity calculated as in Acharya and Pedersen (2005) and calculated as the residuals of an AR(2) process. BONDILLIQINNOV is the innovation in bond market illiquidity using short maturity on-the-run treasuries bid-ask spread as in Goyenko(2006), and calculated as the residuals of an AR(2) process.

| Normal - Regime 1 | Coeff | $\sigma$ | $Coeff * \frac{\sigma_{factor}}{\sigma_{return}}$ |
|---|---|---|---|
| IG Return | | 98.87 | |
| IG * Term | 0.35 | 297.20 | 106% |
| IG * Default | 0.37 | 176.57 | 67% |
| IG * Illiqinnov | 17.80 | 0.18 | 3% |
| IG * Bondilliqinnov | -1.39 | 0.37 | 0.5% |
| Junk Return | | 116.40 | |
| Junk * Term | 0.28 | 297.20 | 72% |
| Junk * Default | 1.11 | 176.57 | 168% |
| Junk * Illiqinnov | -16.04 | 0.18 | 2% |
| Junk * Bondilliqinnov | -11.77 | 0.37 | 4% |
| **Stress - Regime 2** | **Coeff** | $\sigma$ | $Coeff * \frac{\sigma_{factor}}{\sigma_{return}}$ |
| IG Return | | 159.77 | |
| IG * Term | 0.52 | 356.62 | 116% |
| IG * Default | 0.97 | 296.37 | 179% |
| IG * Illiqinnov | 47.15 | 0.21 | 6% |
| IG * Bondilliqinnov | 22.39 | 0.52 | 7% |
| Junk Return | | 254.74 | |
| Junk * Term | 0.43 | 356.62 | 60% |
| Junk * Default | 1.00 | 296.37 | 116% |
| Junk * Illiqinnov | -247.61 | 0.21 | 20% |
| Junk * Bondilliqinnov | -62.33 | 0.52 | 13% |

**Table 5: Regime Switching probability regressions**

This table provides OLS regressions between the estimates of $P(s_t = 2 \mid s_{t-1} = 2) = q$ from the estimation in Table 3 interpreted as the probability of being in the high illiquidity regime and other economic variables. Logit model uses a dummy variable if the probability of being in the high illiquidity regime is greater than 70%. Odd (even) numbered Specification are OLS (Logit) estimations with one period lagged RHS variables. SW is the Stock and Watson recession index with positive numbers indicating growth above trend. $P_{recession,Hamilton}$ is the result of the markov switching model for the quarterly growth rate in US GNP ($y_t$). Following Stock and Watson's (2001) observation of a structural break in the GNP series in 1984, we estimate the model for two distinct time periods : till 1984 and from 1985 to 2007. We use these models to estimate the probability of being in regime 1 (interpreted by Hamilton(1989) as the recession regime) greater than 70%. Market return (negative) is a dummy variable that equals one for three consecutive months of negative market return, where market return is measured as the CRSP Value weighted return with dividends. NBER is a dummy variable that equals for NBER recession dates. The (ADS) business conditions index is based on the framework developed in Aruoba, Diebold and Scotti (2009). The average value of the index is zero. Progressively bigger positive values indicate progressively better-than-average conditions, whereas progressively more negative values indicate progressively worse-than-average conditions. The sample is from January 1973 through December 2007. ILLIQ is the detrended stock market illiquidity calculated as in Acharya and Pedersen (2005). BONDILLIQ is the detrended bond market illiquidity using short maturity on-the-run treasuries bid-ask spread as in Goyenko(2006). ΔVolatility is defined as log of the the square root of the sum of the squared returns on the CRSP value weighted index with dividends, computed for each month using daily returns in that month divided by the square root of the sum of the squared returns on the CRSP value weighted index with dividends, computed for the previous month using daily returns in that previous month. Paper bill spread is the difference between the yield on the 3 month non financial commercial paper rate and the 3 month treasury bill secondary market rate. EE measure is the growth in broker dealer balance sheet over the previous 12 months as calculated by Etula (2009).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Const. | .32*** | -.93*** | .39*** | -.61*** | .26*** | -1.25*** | .30*** | -1.10*** | .46*** | -.31*** |
| | (.02) | (.12) | (.02) | (.11) | (.03) | (.15) | (.03) | (.18) | (.02) | (.11) |
| NBER Recession$_{t-1}$ | .52*** | 2.64*** | | | | | | | | |
| | (.05) | (.38) | | | | | | | | |
| SW Index$_{t-1}$ | | | -.14*** | -.75*** | | | | | | |
| | | | (.02) | (.13) | | | | | | |
| Prob(Recession)- Hamilton$_{t-1}$ | | | | | .40*** | 1.87*** | | | | |
| | | | | | (.05) | (.27) | | | | |
| Negative Market Return$_{t-1}$ | | | | | | | .28*** | 1.74*** | | |
| | | | | | | | (.08) | (.52) | | |
| Business Conditions Index$_{t-1}$ | | | | | | | -.16*** | -.97*** | | |
| | | | | | | | (.02) | (.18) | | |
| Paper Bill Spread$_{t-1}$ | | | | | | | .001*** | .005** | | |
| | | | | | | | (.0004) | (.002) | | |
| Illiq$_{t-1}$ | | | | | | | | | .59*** | 3.06*** |
| | | | | | | | | | (.07) | (.47) |
| Bond Illiq$_{t-1}$ | | | | | | | | | -.04** | -.13 |
| | | | | | | | | | (.02) | (.10) |
| Obs. | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 | 419 |
| $R^2/PseudoR^2(\%)$ | 17 | 13 | 10 | 8 | 12 | 9 | 18 | 14 | 14 | 10 |

| | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|
| Const. | .12 | -2.24*** | .22*** | -1.55*** | .21*** | -1.64*** |
| | (.09) | (.39) | (.06) | (.38) | (.06) | (.38) |
| NBER Recession$_{t-1}$ | | | .28*** | 1.93** | | |
| | | | (.08) | (.81) | | |
| SW Index$_{t-1}$ | | | .009 | .06 | -.01 | -.10 |
| | | | (.03) | (.23) | (.03) | (.23) |
| Prob(Recession)- Hamilton$_{t-1}$ | | | .14** | 1.03** | .18*** | 1.20*** |
| | | | (.06) | (.48) | (.06) | (.47) |
| Negative Market Return$_{t-1}$ | | | .05 | .72 | .11 | 1.15* |
| | | | (.08) | (.62) | (.08) | (.65) |
| Business Conditions Index$_{t-1}$ | | | -.08** | -.67** | -.11*** | -.89*** |
| | | | (.04) | (.32) | (.03) | (.32) |
| Paper Bill Spread$_{t-1}$ | | | .0004 | -.0000788 | .0009** | .003 |
| | | | (.0004) | (.004) | (.0004) | (.003) |
| Illiq$_{t-1}$ | | | .32*** | 2.41*** | .31*** | 2.35*** |
| | | | (.07) | (.59) | (.07) | (.59) |
| Bond Illiq$_{t-1}$ | | | -.07*** | -.42*** | -.07*** | -.36*** |
| | | | (.01) | (.10) | (.01) | (.10) |
| EE measure$_{previousyear}$ | -21.83*** | -218.73*** | -18.28*** | -172.39*** | -19.77*** | -179.55*** |
| | (6.54) | (52.70) | (3.99) | (33.17) | (4.04) | (33.91) |
| $\Delta$Equity Volatility$_{t-1}$ | 7.90*** | 48.89*** | 3.62** | 23.57*** | 3.71** | 24.52*** |
| | (2.26) | (10.02) | (1.49) | (7.70) | (1.49) | (7.70) |
| $\Delta$Equity Volatility$_{t-1}$ * EE measure$_{previousyear}$ | 431.81*** | 4483.81*** | 281.15*** | 2526.45*** | 309.78*** | 2690.63*** |
| | (152.18) | (1255.11) | (87.32) | (743.08) | (86.37) | (775.58) |
| Obs. | 419 | 419 | 419 | 419 | 419 | 419 |
| $R^2/PseudoR^2(\%)$ | 24 | 21 | 43 | 37 | 41 | 35 |

**Table 6: Estimation of high illiquidity stress regime - Out of Sample Tests**

This table provides the estimates of an out of sample test that predicts the stress regime - Regime 2 of the markov regime switching model of Table 3 using economic variables. First we fit a model identical to model 16 of Table 5 using all the economic indicators to predict the stress regime using only the data from 1973 January to 1989 December. Using this model and economic covariates we predict the probability of being in Regime 2 for the second half of the sample period (i.e.) 1990 January to 2007 December. This variable is called Predicted Prob(Regime 2) and predicted for January 1990. We then roll forward every month, using the data available till the previous month to predict regime 2 for the current month till the end of the sample. We then present a logistic regression of this variable as the independent variable against the regime as indicated by the regime switching model of table 3 for the second half of the sample. We also present a figure that displays the ROC curve to assess the accuracy of this logit model to predict regime 2, the stress regime. In the Y-axis we plot the true positive rate (sensitivity), i.e. the proportion of actual Regime 2 months correctly classified by the model. In the X-axis we plot the false positive rate (1-specificity), (i.e.) the proportion of not regime 2 months, incorrectly classified as regime 2 months by the model. Points above the diagonal (random guess) indicate good classification results. The area under the curve measures the accuracy of the model.

| | Regime 2 (as per Regime Switching Model 1990-2007) |
|---|---|
| Constant | -2.55$^{***}$ |
| | (.32) |
| Predicted Prob(Regime 2) | 5.27$^{***}$ |
| | (.74) |
| Obs. | 216 |
| $PseudoR^2$(%) | 27 |

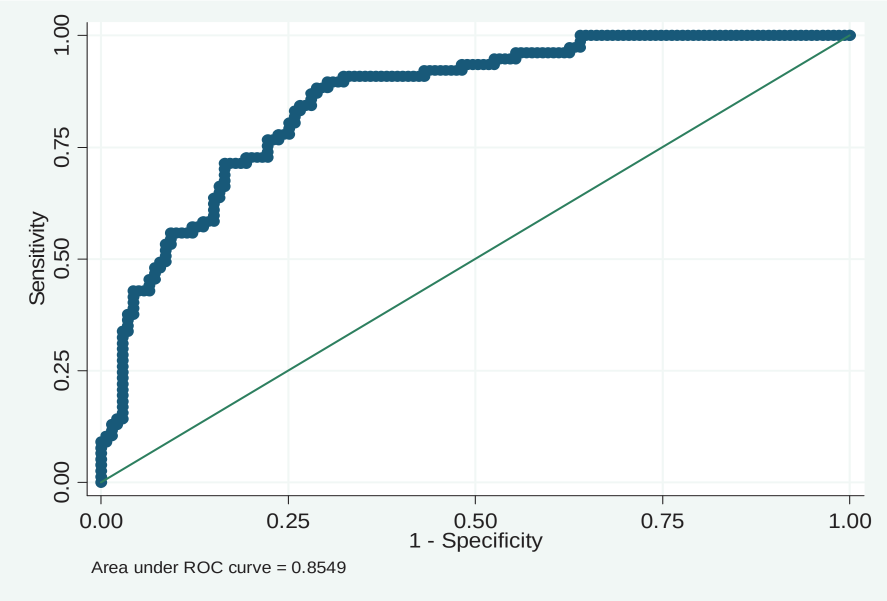


**Table 7. Out of Sample Predictions during the Financial Crisis of 2008**.
For details on the regime switching model refer Table 3. We use the model to estimate the probability of being in regime 2 interpreted as the high illiquidity regime. With this as the LHS variable, we use lagged macro factors to predict this probability using specification 16 of Table 5. This model predicts regime 2 probabilities out of sample for the year 2008. We then weight the respective regime probabilities with the prediction of bond returns itself for 2008 from the regime switching model of table 3 to obtain the predicted bond returns (in excess of the 30 day T-bill return). Panel A shows the actual investment grade and junk grade bond returns (in excess of the 30 day T-bill return) for the year 2008 and the predicted bond return values in basis points. Panel B shows the regression of the actual bond returns against the predicted bond returns with a test of the slope coefficient = 1.0.

| Panel A | IG bond returns | | Junk bond returns | |
|---|---|---|---|---|
| Date | Actual | Predicted | Actual | Predicted |
| 200801 | -140.7 | -44.1 | -212.4 | -164.3 |
| 200802 | -115.9 | 203.2 | 80.6 | -1.4 |
| 200803 | 56.9 | 233.0 | 315.2 | 162.1 |
| 200804 | -233.5 | 76.5 | -60.7 | 282.1 |
| 200805 | -185.5 | 223.5 | -384.4 | -550.9 |
| 200806 | 21.1 | 51.1 | 40.8 | -56.2 |
| 200807 | 0.2 | 96.9 | -103.8 | 249.0 |
| 200808 | -1192.6 | -957.2 | -1139.9 | -1114.4 |
| 200809 | -211.3 | -576.4 | -1231.1 | -575.8 |
| 200810 | 321.6 | -35.6 | -744.3 | 89.8 |
| 200811 | 1291.3 | 694.0 | 1547.8 | 525.5 |
| 200812 | -181.3 | -534.8 | -101.3 | -838.9 |

| Panel B | Actual IG returns | Actual Junk returns |
|---|---|---|
| Constant | 135.78 | 133.44 |
| | (109.57) | (187.52) |
| Predicted IG returns | 0.96*** | |
| | (.14) | |
| Predicted Junk returns | | 0.88*** |
| | | (.18) |
| Obs. | 12 | 12 |
| $R^2$(%) | 64 | 47 |
| F-test if | 0.03 | 1.67 |
| Slope = 1.0 (p-value) | (0.864) | (0.226) |

**Table 8: Flight to Liquidity Effects**

This table provides OLS regressions between the returns (or yields) of various assets and estimates of $P(s_t = 2 \mid s_{t-1} = 2) = q$ from the estimation in Table 3 interpreted as the probability of being in the high illiquidity regime and other economic variables. 3 month treasury bill yields (column 1, net of the over night fed funds effective rate to remove policy effects) and gold returns (Column 2, measured as the log of the ratio of monthly price of gold this month to the price of gold the previous month, expressed in basis points, obtained from the world gold council) are the two dependent variables. The sample is from January 1973 through December 2007. We use the Lehman Brothers Fixed income database for the period January 1973 to December 1996 and supplement it with data from the Merrill Fixed Income Securities Database for the period January 1994 to December 2007. The default factor (DEF) is defined as the difference between the equally weighted return on all bonds in the database with at least one year to maturity and the return on the average of one year and thirty year long term government bond return series from CRSP. The term factor (TERM) is the difference between the long term government bond return and the one month T-bill return from the CRSP database. We report the regressions with the ILLIQINNOV, and BONDILLIQINNOV variables added ($\beta_i$ & $\beta_{bi}$). ILLIQINNOV is the innovation in stock market illiquidity calculated as in Acharya and Pedersen (2005) and calculated as the residuals of an AR(2) process. BONDILLIQINNOV is the innovation in bond market illiquidity using short maturity on-the-run treasuries bid-ask spread as in Goyenko (2006), and calculated as the residuals of an AR(2) process.

| | -(T-Bill Yield minus Fed Funds) | Gold Return |
|---|---|---|
| | (1) | (2) |
| Const. | 46.82$^{***}$ | 32.03 |
| | (2.75) | (26.48) |
| Prob(Regime 2) | 49.79$^{***}$ | 71.71 |
| | (9.53) | (61.53) |
| Term | | -.14$^{*}$ |
| | | (.08) |
| Default | -.002 | .12 |
| | (.022) | (.49) |
| Illiqinnov | -6.82 | 108.36 |
| | (14.40) | (117.28) |
| Bondilliqinnov | -5.77 | 113.98 |
| | (6.89) | (81.31) |
| Prob(Regime 2) * Term | | -.12 |
| | | (.27) |
| Prob(Regime 2) * Default | -0.07 | -.23 |
| | (.05) | (.56) |
| Prob(Regime 2) * Illiqinnov | -7.79 | -330.34 |
| | (41.69) | (253.19) |
| Prob(Regime 2) * Bondilliqinnov | 61.23$^{***}$ | -519.35$^{***}$ |
| | (19.97) | (189.70) |
| Obs. | 420 | 420 |
| $R^2$ | .13 | .07 |

**Fig. 1,2,3. Time Series behavior of bond returns and bond market factors**

The top panel (Fig.1.) of this figure plots in basis points the returns on corporate bonds by credit rating classes. IG stands for bonds rated BBB and above and junk for bonds rated below BBB. To be included in a credit rating class, the bond must be in the Lehman/Merrill databases, with each bond's return value weighted by the amount outstanding in that month. Return are calculated using quoted prices or trades and matrix prices are discarded. The sample is from January 1973 through December 2007. The middle (Fig.2.) and bottom (Fig.3.) panel of this figure documents the return on the four factor portfolios DEF, TERM, ILLIQINNOV and BONDILLIQINNOV. We use the Lehman Brothers Fixed income database for the period January 1973 to December 1996 and supplement it with data from the Merrill Fixed Income Securities Database for the period January 1994 to December 2007. The default factor (DEF) is defined as the difference between the equally weighted return on all bonds in the database with at least one year to maturity and the return on the average of one year and thirty year long term government bond return series from CRSP. The term factor (TERM) is the difference between the thirty year long term government bond return and the one month T-bill return from the CRSP database. ILLIQINNOV is the innovation in stock market illiquidity calculated as in Acharya and Pedersen (2005) and calculated as the residuals of an AR(2) process. BONDILLIQINNOV is the innovation in bond market illiquidity calculated as in Goyenko(2006) and calculated as the residuals of an AR(2) process . NBER recession dates are also shown.

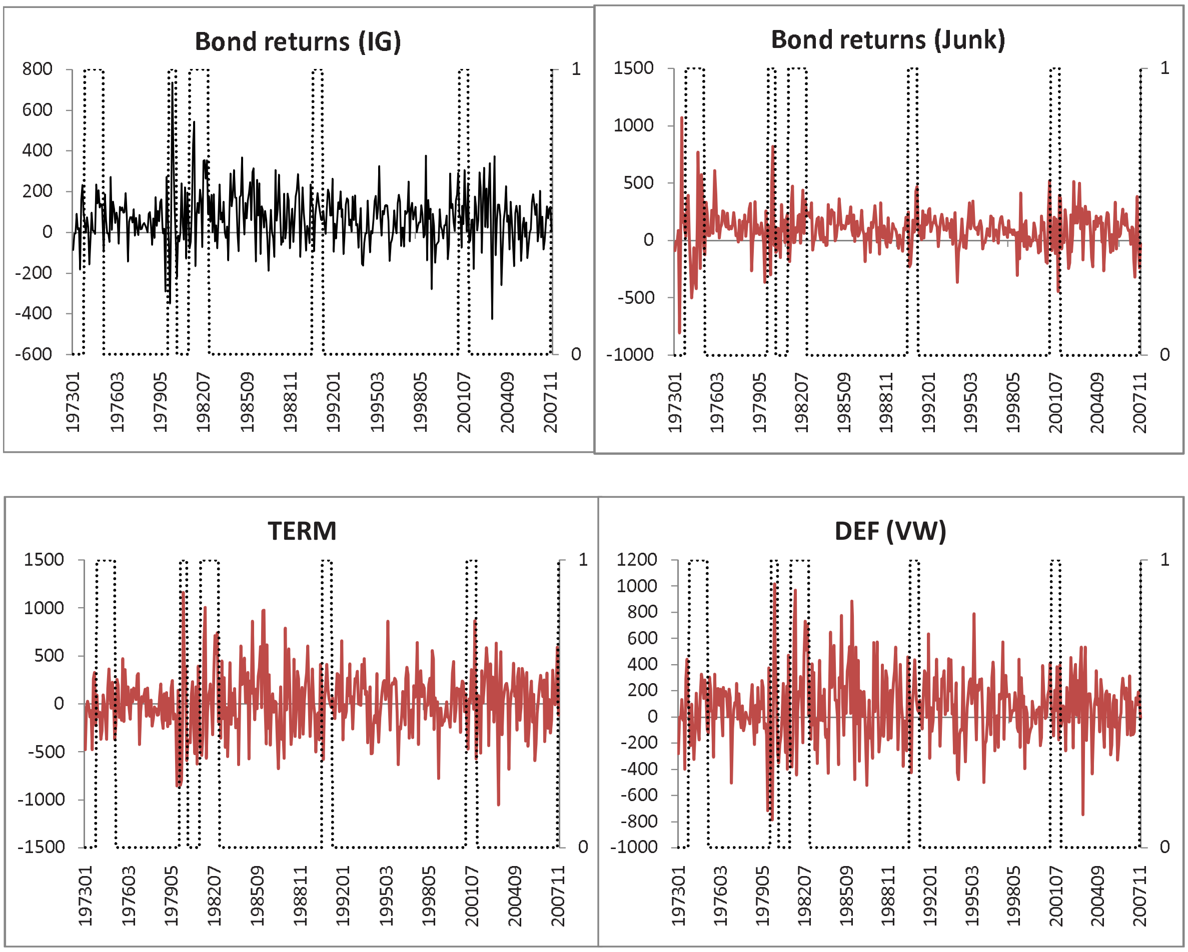
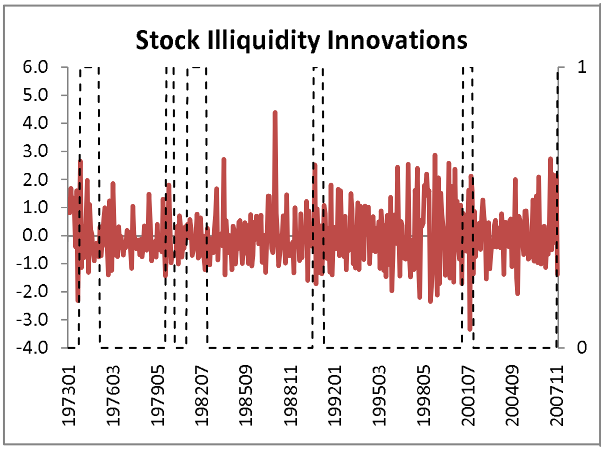


**Fig. 1,2,3 (continued).**



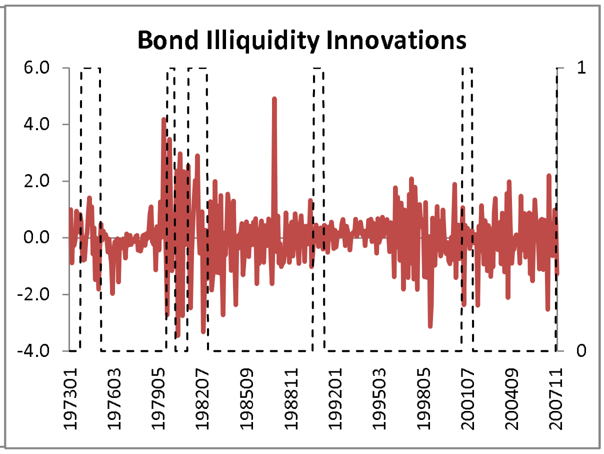



**Fig.4. Probability of high illiquidity regime estimated from a regime switching model**.
For details on the regime switching model refer Table 3. We use the model to estimate the probability of being in regime 2 interpreted as the high illiquidity regime. NBER recession dates are shown.

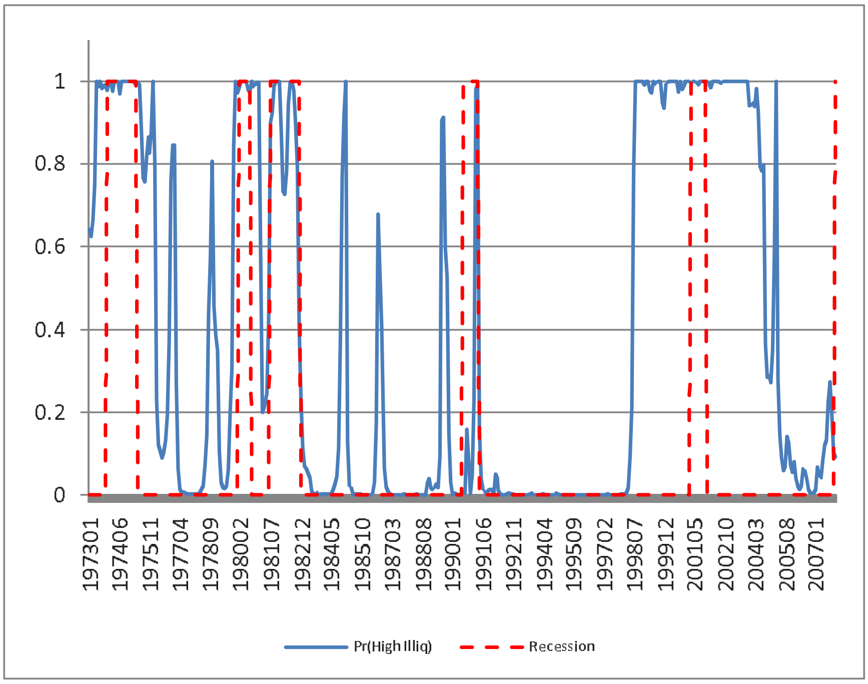


**Fig.5. Regime Switching Model - Out of Sample Predictions during the Financial Crisis of 2008.**
For details on the regime switching model refer Table 3. We use the model to estimate the probability of being in regime 2 interpreted as the high illiquidity regime. With this probability as the LHS variable, we use macro factors to explain this probability using specification 16 of Table 5. This model predicts regime 2 probabilities out of sample for the year 2008. We then weight the respective regime probabilities with the prediction of bond returns itself for 2008 from the regime switching model of table 3 to obtain the predicted bond returns (in excess of the 30 day T-bill return). We plot the actual bond returns (in excess of the 30 day T-bill return) against the predicted bonds returns and compute the RMSE against the the dotted line which assumes a 100% fit and against a regression line. The panel shows the results for junk grade bonds and IG bonds. The analysis above predicts regime 2 probabilities out of sample for the year 2008 using one period lagged macro factors.