Liquidity Risk of Corporate Bond Returns: A Conditional Approach

Viral V. Acharya, Yakov Amihud and Sreedhar Bharath*

This draft: June 13, 2011

*Viral Acharya is C.V. Starr Professor of Finance at New York University Stern School of Business, Research Associate of the NBER and Research Affiliate of the CEPR and the ECGI. Yakov Amihud is Ira Rennert Professor of Finance at New York University Stern School of Business. Sreedhar Bharath is Associate Professor of Finance at Arizona State University. We thank Jason Sturgess and Yili Zhang for diligent research assistance. We are grateful to Banque de France grant for this study, and to Ruslan Goyenko for sharing with us his illiquidity series for the US treasuries. We are grateful for comments from seminar participants at Moody's KMV Annual Credit Risk conference (2007) hosted at NYU Stern, IRC risk management conference in Florence (2008), Arizona State University, Hong Kong University of Science and Technology, McGill, Tel Aviv University, University of Notre Dame , Southern Methodist University, Nanyang Technological University of Singapore, Penn State University, University of Houston, University of Texas at Dallas, University of Virginia (Darden), and University of Toronto (Rotman). All errors remain our own. Contact address: Viral V. Acharya, 44 West 4th St., Suite 9-84, New York, NY - 10012. Tel: (1) 212 998 0354. e-mail: vacharya@stern.nyu.edu. Yakov Amihud, 44 West 4th St., Suite 9-190, New York, NY - 10012. Tel: (1) 212 998 0720. e-mail: yamihud@stern.nyu.edu. Sreedhar Bharath, 325 E. Lemon Street, Suite BAC 542, Tempe, AZ - 85287. Tel: (1) 480 965 6855. e-mail: sbharath@asu.edu.

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Abstract

We study the exposure of the U.S. corporate bond returns to liquidity shocks of stocks and treasury bonds over the period 1973-2007 in a two-regime switching model. In one regime, liquidity shocks have mostly insignificant effect on bond prices, whereas in another regime, a rise in illiquidity produces significant but conflicting effects: Prices of investment-grade bonds rise while prices of speculative grade (junk) bonds fall substantially. Relating the probability of these regimes to macroeconomic conditions we find that the second regime can be predicted by economic conditions that can be characterized as "stress." These effects, which are robust to controlling for other systematic risks (term and default), suggest the existence of time-varying liquidity risk of corporate bond returns *conditional* on episodes of flight to liquidity. Our model can predict the out-of-sample bond returns for the stress years 2008-2009. Further, we find a similar pattern for stocks classified by their default risk, where too liquidity shocks play a special role in periods characterized by adverse economic conditions.

Keywords: credit risk, credit spreads, default, recession, flight to liquidity.
JEL CLASSIFICATIONS: G12, G13, G32, G33.

1 Introduction

This paper shows that the pricing of liquidity risk in the bond market is *conditional* on the state of the economy, with liquidity risk becoming more important in times of financial and economic distress. Using a regime-switching model, we find a significant (absolute) increase in the exposure (beta) of corporate bond returns – both investment-grade (IG) and junk – to liquidity shocks in stocks and Treasury bonds, after controlling for term and default risks. We provide an econometric time-series model that predicts the economic regimes in which liquidity matters more for asset pricing and use it to generate a conditional forecast of bond returns. Further, we find that stocks sorted on their likelihood of default also exhibit an increase in their (absolute) liquidity betas in times of economic distress.

Liquidity shocks affect realized returns because expected liquidity affects expected returns (Amihud and Mendelson, 1986, 1991). Given the persistence of illiquidity, a positive illiquidity shock raises future expected illiquidity and expected return which in turn lowers prices. This usually generates a negative liquidity beta,[1] though flight to liquidity can produce a positive relation between illiquidity shocks and returns on liquid assets. The relation between illiquidity shocks and returns is documented for stocks by Amihud (2002), it is employed in asset pricing by Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Sadka (2006) and applied for bonds by deJong and Driessen (2007) and Lin, Wang and Wu (2011). This paper contributes to these studies by showing that the the impact of liquidity shocks on asset prices is *conditional*, being significantly stronger in adverse 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,[2] and Watanabe and Watanabe (2008) suggest a regime-switching pattern of the pricing of liquidity risk of stock returns conditional on market liquidity.

In a regression model of bond returns on four pricing factors—term spread returns, default spread returns, and liquidity shocks on stocks and Treasury bonds—we study the response of corporate bond prices to shocks in illiquidity of stocks and Treasury bonds. We show that this response varies over time, switching between two regimes which we characterize as "normal" and "stress." Employing Hamilton's (1989) methodology, we first identify statistically the two regimes between which there are variations in the liquidity betas as well as the betas of

[1] This holds under reasonable assumptions on the asset cashflows; see a formal model in Acharya and Pedersen (2005).

[2] 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).

the term risk and default risk. We then show that these two regimes can be predicted by macroeconomic and financial variables. The regime which we call "stress" is associated with adverse macroeconomic conditions such as recessed economic activity and adverse financial market conditions such as negative stock market returns, heightened volatility and shrinking balance-sheets of financial intermediaries.

Employing our economic prediction model of being in the normal or in the stress regime, we provide *out-of-sample* forecast of corporate bond returns for the years 2008-2009. In regressions of monthly realized returns on predicted returns, R^2 is 76% and 77% for junk and IG bonds, respectively, and the coefficients on predicted return are close to one and the intercepts are close to zero. As shown in Figure 5, the predicted return does a reasonable job at predicting the returns 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 for the second half of the sample,[3] we again obtain that the prediction has significant power with an accuracy of over 88%.

Importantly, we find that the sign of liquidity betas is quite the opposite for IG and junk bonds in the stress regime: The response of junk bond returns to illiquidity shocks is significantly negative while IG bond returns respond in a positive and significant way. In this regime, there is a greatly significant difference in the return-iliquidity shock relation between IG and junk bonds, whereas in normal regime, this difference is smaller and less significant. This pattern is robust to controlling for maturity and default risk. This suggests that in the stress regime there is a "flight to liquidity" wherein investors prefer (or price more favorably) more liquid assets such as IG bonds rather than the less liquid junk bonds.

This analysis is extended for stocks sorted on the likelihood of default, using Altman's (1968) Z–score as modified by Hillegeist et al. (2004). We form portfolios of high- and low-default risk stocks, analogous to the portfolios of junk bonds and investment-grade bonds, respectively. Similar to our findings for corporate bonds, we identify statistically two regimes which differ between them in the effect of stock liquidity shocks (as well as some other variables). Importantly, we find again that the probability of being in these regimes is predictable by the same macroeconomic variables that predict the liquidity risk regimes for corporate bond returns: There is a positive and significant contemporaneous correlation between the bond-based and stock-based estimates of the probability of the economy being

[3]For each month, we 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 statistically-identified probability of being in the stress regime in that month obtained from the time series regressions of bond returns on the pricing factors.

in the “stress” regime, with the stock-based estimate of the stress regime probability leading the estimated probability of the stress regime for the bond market. We further find that the probability of being in the “stress” regime affects the impact of the market return on the return of Fama and French’s (1993) HML (zero-investment portfolio based on high-minus-low book-to-market ratio), and nearly half of the variability of the HML return is explained by the return on a zero-investment portfolio based on default risk.

Thus, our analysis offers an economic explanation for the HML factor. On the one hand, the HML factor represents time-varying exposure to the market return itself, where the time-variation is conditional on economic and financial stress variables. On the other hand, this time-variation is adequately captured by a default-risk factor, which in turn we showed represents time-varying liquidity risk, again conditional on economic and financial stress variables. We conclude that the HML factor or the value premium potentially reflects the conditional liquidity risk of high versus low default-risk stocks.

In summary, our conditional approach to modeling the liquidity risk of securities exposed to default risk yields rich and novel explanations for understanding asset prices.

The paper proceeds as follows. Section 2 describes the data we employ. Sections 3 and 4 present results for our unconditional and conditional liquidity risk tests, respectively. Section 4 also reports results of the out-of-sample tests. Section 5 presents results on stock portfolios constructed according to the likelihood of default. Section 6 discusses additional related literature. Section 7 offers final conclusions.

2 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 over the period January 1971-March 1997. We use the data from the 1973-1997 period when coverage became wide spread. This is the database used by Elton et al. (2001) to explain the yield spread on corporate bonds, and 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.

This study uses a subset of the data in the Warga database by employing several selection criteria. First, we include only bonds that were priced by traders or dealers and eliminate bonds that were matrix priced.[4] This rule is similar to that behind the CRSP government bond file, which is the standard academic source of government bond data. Next, we eliminate all bonds with special features that would result in them being priced differently. This means that we eliminate all bonds with options (e.g. callable bonds or bonds with a sinking fund), with floating rates, 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 indicated 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.

These data are supplemented by data on monthly prices of corporate bonds that are included either in the Merrill Lynch Corporate Master index or in 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 selection criteria used for the Lehman database were also used with the Merrill database. Thus, during the overlapping period between the two databases (December 1996 to March 1997), the constituent bonds in the two databases are nearly identical. In the Lehman database all bonds have missing data in August 1975 and December 1984, and their prices are replaced by interpolated prices. Most bond issues are rated by both S&P and Moody's and the ratings agree with each other. We eliminate unrated bonds and bonds whose rating by S&P and Moody's is not the same for the broad letter-based categories.

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

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

P_{τ} is the quoted price in month τ; AI_{τ} 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 $\tau + 1$. For the bond return indexes that we use, we value weight the monthly returns of all eligible bonds in each rating class by the total amount outstanding of each bond. This reduces significantly price errors for particular bonds. In our sample over the period 1973-2007, there were on

[4]For actively traded bonds, dealers quote a price based on recent trades of the bond. We eliminate bonds for which a dealer did not supply a price because they 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. For matrix prices, all that our analysis uncovers may be the rule used to matrix-price bonds rather than the economic influences at work in the market.

average 2,234 bonds in each month, with a minimum number of of 245 and a maximum number of 9,286. The maximum number of months in our sample period is 420, but data are missing for some rating classes in some months.

ENTER TABLE 1

Table 1 Panel A reports the summary statistics of the returns (in basis points, denoted bps) on corporate bond aggregated into value-weighted indexes by rating classes. As expected, the mean and standard deviation of bond returns are greater for bonds with greater default risk. The monthly mean return on AAA-rated bonds is 67.2 bps with standard deviation of 134.5 bps, and for CCC bonds, the mean and standard deviation are, respectively, 160.3 bps and 332.0 bps. For most of our analysis, we rely on groupings into investment-grade ("IG," BBB-rated and above) and high-yield speculative ("junk," below BBB rated) bonds. For this grouping, we find that the return on IG and junk bonds are, respectively, 67.6 and 97.6 bps and the respective standard deviations are 127.3 and 177.9 bps.

We follow Fama and French (1993) in using two common risk factors for corporate bonds, TERM and DEF, which reflect unexpected changes in the term structure of interest rates and in default risk. Fama and French (1993) justify these choices by an ICAPM setting in which these two factors are hedging portfolios.[5] Following Gebhardt et al (2005), we calculate the factor 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), and the factor DEF 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 return on government bonds. The latter is the average returns on one-year and thirty-year government bonds because corporate bonds in the sample used to construct the DEF factor have maturities from one to thirty years.[6] The equally-weighted corporate bond returns better capture the extreme default outcomes each month.

We add to the model two liquidity risk factors which are innovations in the illiquidity on stocks and bonds. The stock illiquidity index is the market's average price-impact measure of Amihud (2002), as modified by Acharya and Pedersen (2005). It is calculated as the equally-weighted average of the daily ratio of absolute stock return to its daily dollar volume, and averaged over the days of the month to provide the monthly stock illiquidity measure, using

[5]Following the suggestions and results in Gebhardt et al. (2005, footnote 2), we do not include the market factor which they found empirically to have almost no explanatory power for corporate bond returns in the presence of default and term risk factors.

[6]All of our results are qualitatively similar if we use the thirty year Treasury bond return to construct the DEF factor instead of the average of one-year and thirty-year returns.

NYSE and AMEX stocks.[7] The bond illiquidity measure is the equally weighted quoted bid-ask spread on on-the-run short maturity treasuries.[8] The innovations in the stock (bond) indexes are the residuals from an autoregressive model with AR(3) (AR(2)) specification.[9] We call the innovations in the stock and bond liquidity indexes Silliq and Billiq, respectively.

Panel B of Table 1 presents summary statistics on the four factors that we use in this study. The mean risk premium for the default factor (DEF) is 9.5 bps per month with t = 1.72, while the average risk premium for the term factor (Term) is 17.7 basis points per month, which is insignificantly different from zero. The mean of the two liquidity factors is practically zero. Panel C of Table 1 shows the pairwise correlations between TERM, DEF and the two liquidity risk factors. TERM and DEF are highly negatively correlated (correlation = -0.529), whereas the two liquidity risk factors are less correlated with each other (correlation = 0.086), and they are also not highly correlated with TERM and DEF (the correlations of DEF with Billiq is -0.057 and with Silliq it is -0.153). This helps with a clean interpretation of the liquidity risk effects we identify.

ENTER FIGURES 1-3

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 crises, for instance, the 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.

3 Unconditional liquidity risk

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.

[7] To make ILLIQ stationary, the series is modified by the normalization formula due to Pastor and Stambaugh (2003) and Acharya and Pedersen (2005): the ratio of the capitalizations of the market portfolio at the end of month t - 1 and of the market portfolio at the end of July 1962.

[8] These data are as in Goyenko (2006). We thank Ruslan Goyenko for providing us the data.

[9] The AR(3) model with the Shaman Stine (1989) correction for finite sample coefficients, for stock illiquidity is estimated beginning in January 1973 and the bond AR(2) model is also estimated beginning in January 1973, to coincide with the data period. The AR lag length is determined to ensure that residuals are not serially correlated. Results in the earlier version of the paper are similar if we use longer time periods to estimate the innovations

3.1 Methodology and results

First, we estimate the following time-series specification:

$$\begin{aligned} R_{j,t} &= \alpha_j + \beta_{j,T} \times TERM + \beta_{j,D} \times DEF \\ &+ \beta_{j,SI} \times Silliq + \beta_{j,BI} \times Billiq + \epsilon_{j,t} \ , \end{aligned} \tag{2}$$

for $R_{j,t}$ being the value-weighted return on corporate bonds of rating class j in excess of the 30-day T-bill return $j \in \{\text{AAA, ..., CCC \& Below}\}$. This specification is similar to that of Fama and French (1993), augmented with the two liquidity risk factors.

ENTER TABLE 2

Table 2 Panel A presents the coefficient estimates. For all ratings, the loadings on TERM and DEF are positive. The TERM factor loading is statistically significant for all rating classes and it is higher for the IG group of bonds (BBB and higher) than it is for junk bonds because the duration of IG bonds is generally higher. The DEF loadings are monotonically increasing down the rating groups (except for the CCC group), consistent with worse credit quality.

Of primary interest to this paper, the liquidity risk loadings β_{Si} and β_{Bi} for both stocks and bonds, Silliq and Billiq, are negative for all ratings below BBB. This means that when liquidity worsens in either the stock or bond market, junk bond prices tend to fall. In contrast, β_{Si} is positive for all IG bonds and and β_{Bi} is also positive for the higher-rated IG bonds (above A). Overall, the coefficients on liquidity risks are almost monotonically declining from positive to negative values as we move from AAA down to CCC bonds. This pattern suggests a "flight to liquidity" phenomenon: When illiquidity rises, there is a flight from low-rated bonds which are generally less liquid to the more liquid higher-quality bonds. Consequently, the prices of high-rated corporate bonds rise and the prices of low-rated bonds fall. This is in addition to the effect of the default risk, which is captured by the effect of the factor DEF. The explanatory power of our model is reasonably high for BBB and above (adj-R^2 is between 75% and 82%), but it deteriorates substantially for below-BBB bonds (adj-R^2 falls from 51% for BBB to 11% for CCC and below).[10]

[10] de Jong and Driessen (2007) too estimate a model with similar liquidity factors, but they use the stock market excess return instead of our two bond-market-based control variables, TERM and DEF, which render the market factor insignificant (see Gebhardt et al. (2005)). Unlike in our results, their estimated coefficients of the illiquidity factors do not switch from positive for high-rated bonds to negative for lower rated bonds which suggests flight to liquidity, and their liquidity factors coefficients are not as monotonic in the rating classes as we show them to be.

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 and the coefficients estimated in Panel A of Table 2. For BBB and above, the liquidity risks are not economically significant: a one standard deviation shock to liquidity risks produces a meagre 0.6% to 9% of standard deviation in returns for these rating classes. The effects of TERM and DEF appear much more significant than those of liquidity risks for BBB and above, with the effect of TERM being the largest. But for junk bonds (BB and below), liquidity risk has greater economic significance for bond returns than its significance for IG bond returns (between 10% to 40%), while the effect of TERM declines. Surprisingly, the effect of DEF does not rise substantially for bonds with rating lower than BBB.

In summary, Table 2 makes it clear that there is unconditional liquidity risk in corporate bond returns, which is substantially higher for junk bonds than it is for investment grade bonds. The switching signs of the liquidity risk as we move from high-rated to low-rated bonds suggests the phenomenon of flight to liquidity which we analyze in greater detail below.

4 Conditional liquidity risk

Most of the current academic literature has focused on *unconditional* liquidity risk as we have also analyzed thus far. However, recent theoretical literature suggests that market liquidity and its impact on asset prices should be *conditional* as they fluctuate due to funding conditions. Brunnermeier and Pedersen (2009) show that funding illiquidity in the market adversely affects market liquidity when negative wealth shocks make margin constraints binding for financial intermediaries and force liquidations, or if margin constraints rise in times of higher volatility. Acharya and Viswanathan (2011) provide an endogenous link between wealth shocks and adverse market illiquidity. In their model, negative value shocks raise the leverage of financial intermediaries, which in turn can induce their managers to risk-shift ("gamble for resurrection") in order to gain at the expense of debt holders. As these firms need to roll over their short term debt which continuously matures, they become capital constrained because lenders are less willing to provide capital, knowing the risk-shifting propensity of the managers. Then, highly leveraged intermediaries are forced to liquidate their risky positions and asset markets can clear only at "cash-in-the-market" prices (see

Shleifer and Vishny (1992), Allen and Gale (1994, 1998)). He and Krishnamurthy (2010) consider households which invest through intermediaries. Then, a negative wealth shock makes households rebalance their portfolios and allocate money away from risky to riskless assets, thus lowering intermediary wealth, causing capital constraints on intermediaries and forcing asset sales and systemic liquidity problems.

This recent literature suggests that a given market liquidity shock generates greater effect on asset prices following negative wealth shocks to the economy (which are generally coincident with a rise in aggregate volatility) and especially shocks to financial intermediary capital. In normal times, liquidity shocks can be absorbed by financial intermediaries as they are far from their funding constraints and thus have ready capital for this purpose. But in times of adverse economic and financial sector stress, financial intermediaries become more capital-constrained. Then, a given-size liquidity shock generates a greater effect on asset prices because liquidity providers are constrained all at the same time and require a higher liquidity premium, which in turn means greater asset price discount for a given liquidity shock. Further, in a bid to improve the liquidity of their balance sheets in such times, financial intermediaries exhibit greater aversion to holding less liquid assets and opt for more liquid ones.

This generates a link between adverse economic shocks and financial sector stress on the one hand and the return-liquidity risk relation on the other. Of particular relevance to corporate bonds is the fact that financial institutions are usually the marginal price-setters in these markets, so that this link should be more pronounced.[11] We therefore test the following conditional effect of liquidity risk on corporate bonds: In episodes of adverse economic conditions, a rise in market illiquidity leads to a decline in all bond prices; however, in such periods investors substitute from less liquid to more liquid bonds, so that the effect of liquidity risk is exacerbated for less liquid (junk) bonds, while liquid (investment grade) bonds become more desirable.[12]

4.1 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

[11] This intuition is consistent with Garleanu and Pedersen (2009) who show that an asset's required return depends not only on traditional risk factors, but also on the asset's exposure to conditions that cause some of its marginal investors to face rising funding constraints, and on the share of such constrained investors among the asset holders.

[12] Amihud (2002, p. 45) provides a similar analysis for stocks.

there is a set of times when betas are substantially different than in 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 of regime switching in the pricing of liquidity risk of stocks.

4.1.1 Methodology

We estimate a Markov regime-switching model for corporate bond betas as follows, allowing the intercepts and the slope coefficients (betas) of bond return models to potentially vary between two regimes. The model also allows the variance-covariance matrix to change between the two regimes.We use two value-weighted returns (based on face value outstanding) on two bond portfolios, one of investment grade (IG) bonds and one of junk bonds.

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:

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

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:

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

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, χ^2_W has an asymptotic chi-squared distribution with r degrees of freedom where r is the rank of L and V is 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 across the two regimes.

4.1.2 Results

The results in Table 3 Panel A show a clear pattern of two regimes in IG and junk bonds with the factor betas varying, especially for the two liquidity variables. In Regime 1, the two liquidity betas are statistically insignificant for IG bonds while Silliq alone is significant for junk bonds. Note that any common effect of liquidity on IG and junk bonds is indirectly captured by the factor DEF, so that the liquidity effect that we document is possibly weaker than its full direct effect (this is further discussed below in Section 5.4). Nevertheless, the liquidity betas in regime 2 present quite a different picture. For junk bonds, the two liquidity betas turn highly negative and statistically significant. The beta of Silliq rises threefold and that of Billiq rises fivefold compared to their magnitude in regime 1, both becoming statistically significant. In contrast, for IG bonds, both liquidity betas become highly *positive* and statistically significant and rise threefold to elevenfold. In other words, the liquidity shocks affect bond prices in opposite ways in regime 2, depending on the bonds rating. IG bonds, which are more liquid, become more desirable if illiquidity rises while junk bonds that are less liquid become less desirable, with the effects being statistically significant in both ways. This effect is consistent with "flight to liquidity" in regime 2.

Panels B and C of Table 3 show significant changes in the liquidity betas. Of particularly noticeable is the *opposite* directions in the changes in the liquidity betas in regime 2 between IG and junk bonds. Then, the Silliq beta for IG bonds, which is insignificantly different from zero in regime 1, become more than four times larger and significant, whereas the Silliq beta which is negative and significantly in regime 1 becomes nearly three times more negative and more significant. The same pattern is observed in for changes in the Biliq betas in regime 2. For IG bonds, the Billiq beta becomes positive and significant while for junk bonds it becomes more negative and significant. While in regime 1 the differences in Billiq betas between IG and junk bonds is insignificant, it becomes quite signicant in regime 2 (see panel C). Tests of the difference in coefficients between IG and junk bonds in the two regimes, presented in Panel C, show that the differences are most significant in regime 2. It is in regime 2 that the effect of liquidity shocks on corporate bonds is polarized, raising IG-bond prices and lowering junk bond prices.

ENTER TABLE 3

The factors TERM and DEF too have some of their coefficients change between regimes. Notably, while the beta of DEF rises in regime 2 for IG bonds, it remains practically unchanged for junk bonds, which is quite striking, since junk bonds are more vulnerable to default risk. Comparing IG and junk bonds in regime 2 (see Panel C), we note that while there is a significant difference between the effect of DEF on their values in regime 1, this difference disappears in regime 2. Then, both IG and junk bonds are equally affected by DEF, in spite of their different likelihoods of default. The same applies to the betas of TERM: in regime 1, they are significantly different between IG and junk bonds while in regime 2 there is not significant difference between them.

The picture that emerges from the results is as follows:

1. There is a sharp difference in regime 2 between the effect of liquidity shocks on prices of IG and junk bonds, with the effects going in opposite directions, being positive for IG bonds and negative for junk bonds. This directional and statistical difference is absent in regime 1.

2. There is no difference in the effect of TERM and DEF between IG and junk bonds in regime 2, while in regime 1 there is a significant difference between them.

Next, we assess the contribution of the regime switching model to the in-sample accuracy of estimation by regressing actual bond returns in each regime on predicted returns. Ideally, the intercept in this regression should be zero and the slope coefficient should obviously be 1. We generate predicted returns in two ways: (a) from the regime switching model for that regime, and (b) from an unconditional model whose coefficients are the same for the entire sample period, obtained by estimating our model with fixed coefficients over 1973-2007.

Table 3 Panel D shows the estimated coefficients from the regression of actual returns on predicted returns. There are 4 regressions: for each of the two regimes, we do a regression for IG and junk bonds. Whereas the conditional model produces predicted returns that result in a slope coefficient of practically 1 (as trivially expected) and an intercept of zero, the predicted returns from the unconditional model result in a slope coefficients which is away from 1. In regime 1, the coefficients of the predicted returns are significantly below 1.0 for both IG and junk bonds, meaning an underestimation of positive returns and overestimates of negative returns. In regime 2, it is the opposite. The predicted slope coefficient is greater than 1, implying that the predicted returns overestimate positive returns and underestimate negative returns. Altogether, the results from this table show the extent of improvement in the predictive power of the model when using our regime-switching regression.

As for the economic significance of the effect of liquidity risk on bond returns, we obtain that the effect roughly doubles in the stress regime.[13] We measure the economic significance of the liquidity factors as $Coeff * \sigma_{factor}/\sigma_{return}$, where $Coeff$ is the slope coefficient of the respective factor. $Coeff$ and the two standard deviations are calculated separately for regimes 1 and 2. We observe that the economic significance of the effects of the two liquidity factors, Silliq and Billiq, is quite low in regime 1 but it greatly rises in regime 2. For IG bonds, the effect of Silliq rises from 2% to 8% and that of Billiq rises from 0.9% to 7%. For junk bonds, the rise in the effect of Silliq is from 8% to 14% and for Billiq the rise is from 4% to 13%.

4.1.3 The economic identification of regimes: Stress and macroeconomic factors

So far we have derived the regimes from a purely *statistical* procedure without any economic input. The greater sensitivity of bond prices to default risk and liquidity risk in regime 2 suggests that regime 2 is associated with periods of economic stress. We now formally investigate this important issue. We undertake an *economic identification* of the regimes, using macroeconomic variables and confirm that regime 2 is indeed associated with economic

[13]Detailed results are available upon request.

conditions that can be collectively defined as "stress."

ENTER FIGURE 4

In Figure 4, we plot the model-implied probability of being in the stress regime.[14] The stress regime picks up most data points of being in a recession during the 1970's (picking up the oil-price shock of mid 70's and the high interest-rate regime of late 70's) and early 1980's (again, during the high interest-rate environment) and the financial market stress and the ensuing 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, and does not identify mid 90's as a stress period. Yet, the Russian default and LTCM episode of 1998 are identified as being in the stress regime. The collapse of the internet bubble in March 2000 and the economic downturn that followed (including the aftermath of the 9/11/2001 attack) are also identified as stress regime. Finally, the probability of being in stress regime rises starting 2007 but not as dramatically (we later present out-of-sample analysis for 2008-2009).

We formally estimate the economic determinants of being in regime 2 by a multivariate regression model where the dependent variable is the probability of being in regime 2, denoted $P2$. This probability is modeled as a function of economic and financial variables associated with market conditions and business cycles with (at least) one-month lag. These variables are as follows (described in greater detail in Appendix I):

(i) NBER recession dummy variable: equals 1 in quarters defined by the NBER to be a recession. We exclude this variables from some of our estimations because the NBER declares a recession ex post with significant delay, while we want the information about the variables to be contemporaneous.

(ii) SW Index: the Chicago Fed's CFNAI index (a follow up measure of the Stock and Watson (1989, 2002) recession index). Larger numbers indicate better business conditions.

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

(iv) Negative market return dummy variable: equals 1 if there have been three consecutive months of negative market return (including the given month), based on the CRSP value weighted market return.

[14] This probability of being in state 2 is calculated at time t as the sum of two products: the product of the transition probability from state 1 to state 2 with the probability of being in state 1 at time t-1, and the product of the transition probability from state 2 to state 2 with the probability of being in state 2 at time t-1. This sum is then multiplied by the ratio of the density under state 2 at time t to the conditional density of the t^{th} observation. See Hamilton, 1994 for details.

(v) Business Conditions Index, due to Aruoba, Diebold and Scotti (2009): It is designed to track real business conditions at high frequency. The average value of this index is zero. Bigger positive values indicate better-than-average conditions.

(vi) Paper-Bill spread: the difference between the 3-month non-financial commercial paper rate and the 3-month T-bill secondary market rate. This spread indicates adverse financial and economic conditions

(vii) TED spread: the difference between the interbank loan rate and the T-bill rate. This spread indicates adverse financial and economic conditions. Since the TED spread is highly correlated with the paper bill spread we use the component that is orthogonal to the paper bill spread.

(viii) EE measure: the growth in balance-sheet of broker-dealers, as a measure of risk appetite of financial intermediaries (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 variable 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, we use the growth rates based on past one year's data. A rise in EE measure indicates expectations of good business conditions. However, when growth in this variable is coupled with equity market volatility, it indicates worsenng conditions and involuntary increase in broker-dealer inventory.

(ix) Equity market volatility: the square root of the monthly average of the squared daily returns on the CRSP value weighted index with dividends.

We do a pair of tests using two dependent variables. One is the probability of regime 2 for month t, $P2_t$ which is estimated from our regime-switching model (see Hamilton (1994)) . We employ a standard logit transformation of this probability, $log[(P2_t + c)/(1 - P2_t + c)]$, where $c = 0.5/419$ is a constant that is added in order to accommodate the cases where we estimate $P2 = 1$ or $P2 = 0$.[15] The second is a dummy variable that equals 1.0 if $P2_t > 0.70$ (this threshold is also used by Hamilton (1989)). The first model is estimated by OLS and the second by logit.

ENTER TABLE 4

The estimation results, presented in Table 4, show that regime 2 is associated with economic downturns. The signs of all the macroeconomic and financial variables are consistent with the probability of regime 2 being higher in times of adverse economic conditions. We

[15]See Cox (1970, p. 33).

obtain positive coefficients for the NBER recession, Prob(Recession) - Hamilton, Negative Market Return dummy, Paper-Bill spread, TED spread and Equity Volatility. These variables increase in value under economic stress. In addition, we obtain negative coefficient for SW Index and Business Conditions Index, which rise in value in economic upturn, so their negative coefficients say that the probability of regime 2 is associated with economic downturn. The negative coefficient of the EE measure suggests that as broker-dealers foresee the good times and increase their inventories, or increase their risk appetite when the economy is headed into good times, regime 2 is less likely. But the interaction between Equity volatility and the EE measure is positive and significant). This means that in time of high volatility, a rise in the EE measure may indicate involuntary increase in intermediaries' inventories which is associated with a greater likelihood of the stress regime, which subsequently induces de-leveraging events as observed in 2007 and 2008 in financial markets.

In general, the robust conclusion that emerges is that regime 2 is associated with worsening macro economic and stock market returns. Hence, we call it the "stress" regime and regime 1 the "normal" regime. When employed in isolation, the explanatory power (R^2) of the regime determinants is of the order of 11% to 28%. When all variables are used to explain the model-implied probability of being in the stress regime, the R^2 exceeds 40%. In the model with all variables (excluding the NBER recession dummy, which is known only ex post), those that emerge as having the greatest statistical significance are Prob(recession) - Hamilton, Business Condition Index, TED spread, EE measure, Equity volatility and the interaction of the last two. In the logit regression with the stress regime dummy variable, the variable Negative Market Return dummy also becomes significant.

These results provide a measure of confidence that our regime-switching results on liquidity betas of bonds (Table 3) have sound economic foundations. In this light, it is clearer why in regime 2 – the stress regime – there is greater sensitivity of bond returns to liquidity shocks and why IG bond returns become more sensitive to DEF, the default risk factor.

4.2 Out of sample regime prediction during 1990–2007

The economic foundations of the stress regime (regime 2) enable us to predict its probability based on economic time series and subsequently to predict corporate bond returns. We provide a prediction of the probability of being in regime 2 of the Markov regime switching model of Table 3 using the economic variables identified in Table 4. First, we fit a model similar to the model (14) in Table 4, using all the economic indicators except the NBER dummy (given its ex post nature) to predict the stress regime, employing only the data for the first half of our sample period, 1/1973 to 12/1989. After estimating the coefficients in this model, we predict the probability of being in the stress regime, $\hat{P}2$, for the second half of the sample period, 1/1990 to 12/2007, using a rolling estimation, month by month. That is, we roll forward every month, then using the data available until the previous month develop a predictive model for the stress regime until the current month, and then use this model to predict stress regime for the current month, repeating this process until the end of the sample. For example, we predict the stress regime for the month 1/1990 using data until 12/1989 and coefficient estimates of a model similar to model (14) in Table 4. Then, for month 2/1990, we use all data until 1/1990 to re-estimate this model and generate $\hat{P}2$, and so on.

After having obtained the series $\hat{P}2$ for the period 1/1990-12/2007, we do a logit regression of the likelihood of being in regime 2, obtained from our statistical model of Table 3, Panel A, on the predicted probability $\hat{P}2$. The dependent variable is a dummy variable that equals 1 if the actual probability of being in regime 2, estimated from the regime switching model, is above 70%.

ENTER TABLE 5

The results in Table 5 show how well the likelihood of being in regime 2 is predicted by the economic series-based estimated regime-2 probability $\hat{P}2$. The coefficient of $\hat{P}2$ is positive and significant, and its pseudo R-squared is 27%. We demonstrate the performance of the model by its accuracy in discriminating regime 2 months from normal months, employing 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 are some fraction of cases with the stress months correctly classified as "True Positive" (TP) and some fraction of cases with the stress months classified "False Negative" (FN). Also, some fraction of normal months will be correctly classified as non-stress months or "True Negative" (TN) while some fraction of normal months will be classified as stress months or "False Positive" (FP). In a ROC curve, the TP rate (Sensitivity) is plotted as a function of the FP rate (1-Specificity) for different cut-off points of $\hat{P}2$. Each point on the ROC plot represents a sensitivity/specificity pair corresponding to a particular decision threshold. A completely random guess would produce a point along a diagonal line (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% specificity, 100% sensitivity).

Therefore the closer the ROC plot is to the upper left corner, the higher the overall accuracy of the test.

We 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 88.81%. 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 high accuracy.

4.3 Out of sample predictions of bond returns during 2008–2009

We now test the accuracy of out-of-sample prediction of bond returns based on our regime-switching model during the financial crisis of 2008 and the relatively less stressed period of 2009. Once again, we predict the probability of a given month during 2008 and 2009 being in the stress regime by using the macroeconomic and financial market variables included in model (14) in Table 6 and the coefficients of that estimation model to obtain the predicted probability of being in regime 2. Then, we calculate the predicted bond returns for each regime in each month of 2008 and 2009 using the coefficients estimated on TERM, DEF and liquidity risk factors in each regime shown in Table 3 Panel A and employing the realized values of TERM, DEF and liquidity risk factors. Finally, we calculate the average return in the month by weighting the regime 1- and regime 2-predicted returns by the respective regime probabilities obtained in the previous step. This weighted average return constitutes the predicted bond return for that month, conditional on the realized values of the four factors.

ENTER TABLE 6

In Table 6 Panel A we document the realized (excess) bond returns in each month of 2008 and 2009 for IG and junk bonds from data on iShares investment grade and high yield bond indices, which are the most recent data available to us.[16] We observe a high concentration of negative junk bond returns in the second half of 2008 and in January of 2009, when the crisis was intense. The table also presents our estimated value of $\hat{P}2$, the regime-2 probability.

[16]The Merrill Lynch data on corporate bonds available to us ends in December 2007

Notably, the period with the cluster of negative returns is also when our model predicts that $\hat{P}2 = 1$ or close to 1. Later in 2009, $\hat{P}2$ is lower and also the bond returns are mostly positive. Also striking is the fact that in the months 10/2008 and 11/2008, where $\hat{P}2 = 1$, the returns on IG bonds are positive whereas those of junk bonds are negative, indicating the phenomenon of "flight to liquidity" which we highlighted earlier.

We test the quality of the predicted returns in a regression model of the actual bond return as function of the predicted bond return. In such a regression with an ideal predictor, the intercept should be zero and the slope coefficient should be 1. The results in Panel B of Table 6 are quite close to these criteria. The slope coefficients on the predicted returns are statistically indistinguishable from 1.0 (at the 0.10 level) for both IG and junk bond grades, and the constant is not different from zero in both these regressions. The regression has a reasonably good fit of 77% for the IG bonds and 76% for the junk grade bonds. The results of this regression, plotted in Figure 5, show that the actual-predicted return relation is close to the 45% line of perfect fit. The RMSE of the regression is very close to the RMSE of the 100% fit, again suggesting that the predicted returns do a good job in explaining the actual returns. It can also be seen that the model is able to predict bond returns reasonably well also during the more stressful period: months of Bear Stearns' collapse (March 2008), Lehman Brothers' bankruptcy (September 2008) and the post-Lehman months (October through December 2008).

Overall, we conclude that our regime-switching model provides a good description of bond returns during the financial crisis year of 2008 as well as the relatively less stressed period of 2009. The model is able to capture the dynamics of corporate bond returns both in regime 2, which in 2008 corresponds to all months except January and June, as well as in regime 1, corresponding to six months in the year 2009.

4.4 Flight to liquidity

One interpretation of our results is that, consistent with the literature on asset pricing with frictions discussed above, stressed macroeconomic and financial conditions make investors more averse to illiquidity shocks and they respond by switching from illiquid to assets, such as junk bonds, to investment-grade bonds which are known to be more liquid.[17] An alternative explanation is that the rise in the effect of liquidity shocks on bond prices proxies

[17] Chen, Lesmond and Wei (2007) show that generally investment grade bonds have lower bid-ask spread (quoted or implied) than junk bonds. Also, the frequency of zero-return days, another common proxy of illiquidity, is of the order of 6-10 percent for investment grade bonds and 20-40 percent for junk bonds.

for heightened investor risk-aversion to extreme events or rare disasters (Rietz, 1988 and Barro, 2006). Such events are argued to affect consumption significantly or are 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) by which increases in aggregate volatility necessitate a reduction in investor holdings of risky assets, which in general equilibrium, implies a reduction in their contemporaneous returns. In what follows, we test for distinct effects of risk and liquidity on bond prices which imply, respectively, flight-to-quality/safety or flight-to-liquidity (or both).

ENTER TABLE 7

In Table 7, we first study how the differential bond return—Junk return minus IG return—is explained by default and liquidity risks in normal times and in times of stress (regime 2). The estimation in column (1) omits the liquidity variables, which are included in column (2). There are two points to note. First, the inclusion of the liquidity variables almost doubles the explanatory power of the model, rising from *Adj* $R^2 = 11\%$ to *Adj* $R^2 = 18\%$. This attests to the importance of liquidity risk in determining the junk-IG differential return. Second, the effect of the two liquidity variables is significant only when Prob (Regime 2), the probability of the stress regime, is higher. The negative and significant coefficients of the liquidity risk factors in stress times indicate flight to liquidity, in addition to the flight to safety which is captured by the negative coefficient of Prob(Regime 2)*DEF.

Note that the factor DEF captures only the common part of the illiquidity effect on IG and junk bond returns, but not the part that is associated with regime 2. In column (3), while both Billiq and Silliq effects are statistically significant, *Adj* R^2 is quite low, only 3%, and the interaction of liquidity factors and Prob (Regime 2) is insignificant. The pattern that emerges is that the default risk is distinct from the liquidity risk, especially in the stress regime.

In the fourth and fifth columns of Table 7, the dependent variable is -(T-bill yield minus FED Funds rate). This variable, wich rises with the price of T-bils, is immune to default risk, reflecting only liquidity risk. It is also immune to policy effects and to maturity risk because the Fed fund rate is for very short term.[18] If a rise in illiquidity generates flight to liquidity, then investors will switch from all types of risk and illiquid investments to short-term T-bills which are the least risky and most liquid instrument. Then, their price will

[18]This is similar to the test of Amihud and Mendelson (1991) on the yield spread between T-bills and Treasury bonds of the same maturity.

rise and their yield will fall and -(T-bill yield minus FED Funds rate) will rise. There are two points to note. First, the inclusion of the liquidity variables considerably increases the explanatory power of the model, from $Adj\ R^2$ of 3% to $Adj\ R^2$ of 12%, demonstrating the importance of liquidity risk. Second, while T-bills' prices rise on average in stress regime (the coefficient of Prob(regime 2) is positive and significant), the T-bills prices rise with an increase in illiquidity only in regime 2—the coefficient of Billiq is practically zero while the coefficient of Prob(regime 2)*Billiq is positive and significant. In other words, Treasury bills behave in a manner that is consistent with the behavior of investment grade bonds. In contrast, T-bill returns do not vary with an increase in default risk in the stress regime (DEF * Prob (regime 2) is insignificant). This is also consistent with a flight-to-liquidity phenomenon rather than a flight-to-quality.

4.5 Flight to liquidity and bond maturity

We expect that the effects of liquidity shocks on bond returns that we have documented are greater for longer-maturity bonds, which have greater duration in the sense of having greater price elasticity to changes in yield. Also, because long-term corporate bonds are less liquid than short-term bonds (see Chen et al. (2007)), we expect that long-term bond returns are more sensitive to liquidity shocks than are short-term bond returns. To test this, we create three portfolios of junk-minus-IG returns for three different maturities: short—less than 4 years to maturity, medium— between 4 and 9 years to maturity, and long—more than 9 years to maturity. We expect that in the stress regime (regime 2), the effects of liquidity shocks will increase with maturity.

The results in the last three columns (6, 7 and 8) of Table 7 are consistent with our expectations. The coefficients of Silliq and Billiq are all negative, because a rise in illiquidity lowers the prices of the less-liquid junk bond, while a rise in Siliq has a less negative effect on the price of the more-liquid IG bonds, and a rise in Biliq even raises the price of IG bonds. The effect of Billiq on the differential return between junk and IG bonds is insignificant in normal times, but in times of stress it becomes more negative and significant, with the effect being stronger for longer-maturity bonds. The coefficient of the interactive term Prob(regime 2)*Billiq declines monotonically from insignificant -28.04 for short-term bonds to a significant -76.95 for medium-term bonds and a significant -104.61 for long-term bonds. Similarly, the coefficient of Silliq becomes more negative and highly significant when considering the interaction term Prob(regime 2)*Silliq. This coefficient falls from -132.14 for short-term bonds to -233.20 for long-term bonds. These effects of liquidity risk are present after controlling for the effect of default risk (captured by the factor DEF), in both normal times and stress times.

5 Conditional liquidity risk in stocks classified by default risk

We extend our examination of conditional liquidity risk to stock returns of firms classified by their probability of default. In particular, we test whether the impact of liquidity shocks on stock returns varies over time, and whether these variations are related to macro-economic and financial conditions of stress.

5.1 Methodology

We construct two portfolios of stock returns (differentiated by default risk) and apply our regime-switching methodology to estimating the factors that affect their return. Every month (between 1973-2007) we classify stocks in the CRSP database (NYSE, AMEX and NASDAQ) into 25 (5x5) portfolios sorted on stock return volatility and on their modified Z-score (an estimate of the likelihood of default). This is done so as not to confound the effect of default with that of volatility, given the positive correlation between them across firms, documented by Campbell et al. (2008), and the negative effect of return volatility on expected return, shown by Ang et al. (2006).[19] For each month we calculate for each stock the modified Z-score,[20] using the most recent accounting data and end-of-month market value data, and the standard deviation of daily stock returns from that month. Then we sort stocks into five equal volatility-based quintiles and within each quintile we sort the stocks into five equal portfolios based on the modified Z-score. We calculate the value-weighed return for each of the 25 portfolios. The "low (high) default risk stock return" is the average return of the five portfolios with the highest (lowest) modified Z-score, respectively. We use an accounting-based measure of default risk in order to avoid issues with stock return-based measures of

[19]We thus follow the methodology of Fama and French (1993, p. 8-9) who construct their HML index so as not to confound the book-to-market effect with the size effect.

[20]The modified Z-score, which relates to that of Altman (1968), follows the specification of Hillegeist et al. (2004): -4.34-0.08*wcta+0.04*reta-0.1*ebitta-0.22*mvliab+0.06*sata. wcta is the ratio of working capital to total assets (COMPUSTAT item (actq-lctq)/atq). reta is the ratio of retained earnings to total assets (COMPUSTAT item req/atq). ebitta is the ratio of earnings before interest and taxes to total assets (COMPUSTAT item (piq+xintq)/atq). mvliab is the ratio of market value of equity to total liabilities (COMPUSTAT item (prccq * cshoq)/ltq). sata is the ratio of sales to total assets (COMPUSTAT item saleq/atq).

default risk, given that our dependent variable is itself a stock return.

We then estimate the following model that includes two sets of equations, one for low default risk stocks and one for high default risk bonds, and allows the coefficients as well as the variance-covariance matrix to change between the regimes.

Low Default Risk Stock Returns (returns in excess of the 30 day T-Bill return):

Regime 1: $r_{Low,t} = \alpha^1_{Low} + \beta^1_{Low,Rm}(R_{m,t} - R_{f,t}) + \beta^1_{Low,T}TERM_t + \beta^1_{Low,D}DEF_t + \beta^1_{Low,Si}Silliq_t + \beta^1_{Low,Bi}Billiq_t + \epsilon^1_{Low,t}$

Regime 2: $r_{Low,t} = \alpha^2_{Low} + \beta^2_{Low,Rm}(R_{m,t} - R_{f,t}) + \beta^2_{Low,T}TERM_t + \beta^2_{Low,D}DEF_t + \beta^2_{Low,Si}Silliq_t + \beta^2_{Low,Bi}Billiq_t + \epsilon^2_{Low,t}$

High Default Risk Stock Returns (returns in excess of the 30 day T-Bill return):

Regime 1: $r_{High,t} = \alpha^1_{High} + \beta^1_{High,Rm}(R_{m,t} - R_{f,t}) + \beta^1_{High,T}TERM_t + \beta^1_{High,D}DEF_t + \beta^1_{High,Si}Silliq_t + \beta^1_{High,Bi}Billiq_t + \epsilon^1_{High,t}$

Regime 2: $r_{High,t} = \alpha^2_{High} + \beta^2_{High,Rm}(R_{m,t} - R_{f,t}) + \beta^2_{High,T}TERM_t + \beta^2_{High,D}DEF_t + \beta^2_{High,Si}Silliq_t + \beta^2_{High,Bi}Billiq_t + \epsilon^2_{High,t}$

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

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

Markov switching probability for state transition:

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

In explanatory variables, we include $R_m - R_f$, the excess return on the "market," which is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) in excess of one-month Treasury bill rate (from Ibbotson Associates). We also include the variables TERM, DEF, Silliq and Billiq. TERM and DEF are documented to have a significant effect on stock returns (see Chen, Roll and Ross (1986) and in Fama and French (1989)). As Fama and French (1989, p. 48) state, "[t]he default spread is a business-conditions variable" and "the term spread is related to shorter-term measured business cycles." Indeed, the term yield spread is shown by Estrella and Mishkin (1998) and by Estrella and Hardouvelis (1991) to be a predictor of real economic activity (in particular, of recessions). The default yield spread (the yield differential between AAA and BAA corporate bond) is used by Bernanke (1983) as proxy for financial and economic crisis. Stock and Watson (2003) review the extensive literature on the use of the default yield spread and of the term yield spread as predictors of output growth. In the context of our model, which estimates the effects of illiquidity shocks on the expected return of stocks, DEF and TERM serve to control for future business conditions which affect firms' expected cash flows.

5.2 Results

The estimation results are presented in Table 8, which is analogous to Table 3 in its structure, with returns on stocks with low and high default risk replacing the returns on bonds that are of investment grade and junk rating, respectively. We obtain that the effect of *Silliq*, which measures shocks in stock illiquidity, is significantly different between the two regimes for both low and high default-risk stocks. The coefficient of *Silliq*, which in regime 2 is negative and significant for both low and high default-risk stocks, is respectively about 2.5 times and 22 times bigger in regime 2 than it is in regime 1. In fact, *Silliq* is the only variable whose effect on stock returns changes significantly between the two regimes for *both* low and high default-risk stocks. The significant rise in the coefficient of *Silliq* in regime 2 highlights the importance of liquidity risk, given that we control for the effects of business conditions and the likelihood of default. The effect of Silliq is also significantly different (at the 10% confidence level) between the low and high default-risk stocks in both regime 1 and regime 2.

ENTER TABLE 8

As to the other variables (except *Billiq*), their coefficients change significantly between the two regimes only for high default-risk stocks. The coefficient of the market excess return rises in regime 2 because in times of economic distress, the value of stocks that are vulnerable to default is more sensitive to the overall well-being of the economy, captured by the market return. The coefficient of DEF, which is a bond-based measure of default risk, rises and turns from being insignificant in regime 1 to being positive and significant in regime 2. The coefficient of TERM is negative because a rise in TERM signifies a decline in the slope of the yield curve, which studies show signifies worsening of economic conditions, and this depresses the returns on high default-risk stocks. The negative relation between TERM and returns on high default-risk stocks more than triples in regime 2, consistent with the notion of regime 2 being associated with economic stress.

While ρ_{St}, the correlation of returns between low and high default-risk stocks, is positive in regime 1, it turns negative in regime 2. This pattern is also obtained for returns on IG and junk bonds (see Table 3). This again suggests that in regime 2 low default-risk stocks become more attractive, inducing flight to quality and to liquidity from high default-risk stocks, whose returns decline. And, as observed in Table 8, the liquidity risk in regime 2 is significantly higher (the liquidity beta is more negative) for high default-risk stocks. The coefficients of *Billiq* for both stock return portfolios are insignificant in both regimes.

5.2.1 The economic identification of regimes: Stress and macroeconomic factors

Next, in Table 9 we estimate the economic determinants of being in regime 2 in the case of stocks by a multivariate regression model, similar to that presented in Table 4 for the case of corporate bonds. The dependent variable is the probability of being in regime 2, denoted $P2$. This probability is modeled as a function of economic and financial variables associated with market conditions and business cycles with one-month lag, same as the ones used for the regime-switching model for corporate bond returns in the paper. The estimation is presented once as an OLS estimation of a standard logistic transformation[21] of $P2$, and the other is a logit estimation of a dummy variable that equals 1.0 if $P2_t > 0.70$ (this threshold is also used by Hamilton (1989)).

ENTER TABLE 9

The estimation results show that regime 2 is associated with economic downturns. The signs of all the macroeconomic and financial variables are consistent with the probability of regime 2 being higher in times of adverse economic conditions. We obtain positive coefficients for the NBER recession, Prob(Recession) - Hamilton, Negative Market Return dummy, Paper-Bill spread, TED spread and Equity Volatility. These variables rise in value under economic stress. In addition, we obtain negative coefficient for SW Index and Business Conditions Index, which rise in value in economic upturn, so their negative coefficients mean that the probability of regime 2 is associated with economic downturn. The negative coefficient on the EE measure suggests that as broker-dealers foresee good times and increase their inventories, or increase their risk appetite when the economy is headed into good times, regime 2 is less likely. But during volatile times, greater broker inventory growth is subsequently

[21] We employ $log[(P2_t + c)/(1 - P2_t + c)]$, where $c = 0.5/419$ is a constant. See discussion of Table 4.

associated with a greater likelihood of the stress regime (the interaction between Equity volatility and the EE measure is positive and significant), similar to the de-leveraging events observed in 2007 and 2008 in financial markets.

When all variables are used to explain the model-implied probability of being in the stress regime (excluding the NBER recession indicator, which is known only ex post), the R^2 is 43% in the OLS regression of the probability of regime 2, and 35% for the logit regression. The evidence thus shows that regime 2, in which illiquidity shocks become significantly more important in pricing stocks of high and low default risk, is associated with worsening macroeconomic and financial sector conditions.

5.3 Relation between stress regimes for bonds and stocks

We also relate our two estimates of the probability of the "stress" regime – regime 2 – which are obtained separately from corporate bond and stock returns. We denote for convenience $Prob(Regime\ 2)_t^{Bond}$, obtained from the estimation of model for bond returns in Table 3, by $BP2$ and $Prob(Regime\ 2)_t^{Stock}$, obtained from model for stock returns in Table 8, by $SP2$. If these series indeed reflect similar economic conditions, we expect them to be highly correlated. Indeed, Tables 4 and 9 show that the series are predicted by the same economic variables. Confirming this, we find that $Corr(SP2_t, BP2_t) = 0.54$, highly significant with a p-value of 0.0000. However, the series $SP2_t$ and $BP2_t$ are both highly serially correlated, so we use their first difference, $\Delta\ SP2_t$ and $\Delta\ BP2_t$, respectively, whose serial correlations are low. Regressing $\Delta\ BP2_t$ on $\Delta\ SP2_t$, the coefficient is 0.11 with t=2.32, statistically significant.[22]

ENTER TABLE 10

We then examine which of the two series of stress regime probability leads the other. We expect that $SP2$ leads $BP2$ because stock prices adjust faster to information than do bond prices. Again, given that the two series are highly autoregressive, we test this hypothesis using the first difference of these series, $\Delta\ SP2$ and $\Delta\ BP2$. We regress $\Delta\ BP2_t$ on $\Delta\ SP2_{t-1}$ and on $\Delta\ SP2^2_{t-1}$, the latter intended to capture the effect of large changes in $SP2$. We also estimate an analogous regression where $\Delta\ SP2_t$ is regressed on $\Delta\ BP2_{t-1}$ and on $\Delta\ BP2^2_{t-1}$. The results in Table 10 show that $\Delta\ SP2_{t-1}$ and $\Delta\ SP2^2_{t-1}$ provide significant prediction of

[22]The test employs the Newey-West (1987) method for robust estimation of the standard error with four lags.

Δ $BP2_t$, but there is no significant prediction of Δ $SP2$ by lagged Δ $BP2$. These results are consistent with our hypothesis.

5.4 A default-risk explanation of Fama and French's (1993) HML factor

We examine the relevance of our estimated $SP2$ in the context of Fama and French's (1993) HML factor, the return differential between stocks with high and low book-to-market ratio (also referred to as the "value premium"). We estimate a regression of HML on $(R_M - R_f)$ and its interaction with $SP2$ and on HML_{def}. Recall that HML_{def} is the return on the portfolio of stocks with high default risk minus the return on the portfolio of stocks with low default risk; these are the portfolios used in the regime-switching model of stocks in Table 8. Campbell et al. (2008) document a negative relation between firms' book-to-market ratio and their probability of default. Consequently, we expect that HML is negatively related to $(R_M - R_f)$ because improvement in business conditions helps more firms in high risk of default, which is negatively related to their book-to-market ratio. The benefit of improved business conditions, reflected in higher $R_M - R_f$, is particularly valuable for stocks with high probability of default in times of economic distress. Therefore, if our estimated regime 2 indeed measures times of economic distress, the interaction term $(R_M - R_f) * SP2$ should have a negative coefficient. Further, $SP2$ should have a positive coefficient because during times of economic distress the probability of default is high, which is associated with HML. Finally, if HML is associated with the probability of default, it should be negatively related to our factor HML_{def}.

ENTER TABLE 11

The results in Table 11 are consistent with our expectations. Consider the estimation in Column 2. The coefficient of $(R_m - R_f)$, which is negative and significant, practically doubles in size when the economy is in regime 2. This is seen from the coefficient of $(R_M - R_f) * SP2$ which is similar in size to that of $(RM - Rf)$, both being negative and significant.[23] The results mean that when being in economic distress, i.e., $SP2 = 1.0$, an excess return of 1% on the stock market raises the value of low book-to-market stocks by nearly 0.5% relative to the value of high book-to-market stocks. The effect is halved when $SP2 = 0$. $SP2$ itself is positive but insignificant.

[23]The estimation employs the Newey-West (1987) method with one lag and robust standard errors.

When HML_{def} is added to the model (Column 3), its coefficient is negative and very highly significant, and the R^2 of the model rises from 0.21 to 0.58. Because HML_{def} already reflects the states of regime 2, the interaction term $(R_M - R_f) * SP2$ becomes insignificant. $SP2$ itself is positive and marginally significant, as expected. The intercept in this specification declines by almost 60% (from Column 2), indicating that more than half of the alpha of HML is explained by economic distress and default-related variables, $SP2$ and HML_{def}.

Finally, we observe that 48% of the variability in HML return is explained by the variability in HML_{def} alone, attesting to the importance of default risk in the explanation of the widely-used HML factor. The mean HML_{def} is negative, -0.53 in our sample, a fact documented among others by Campbell et al. (2008), whereas the mean HML is 0.47 and the intercept of HML in Column 4 in Table 11 is 0.27. The significant negative relation between HML and our HML_{def} and the decline in the estimated value of the intercept suggests that around half of the value premium, estimated by the mean of HML, is due to the excess return of low default-risk stocks over high default-risk stocks.

To summarize, our analysis offers an economic explanation for the HML factor. On the one hand, the HML factor represents time-varying exposure to the market return itself, where the time-variation is conditional on economic and financial stress variables. On the other hand, this time-variation is adequately captured by a default-risk factor, which in turn we showed represents time-varying liquidity risk, again conditional on economic and financial stress variables. We conclude that the HML factor or the value premium potentially reflects the conditional liquidity risk of high versus low default-risk stocks.

6 Related literature on bond yields and liquidity

The effect of liquidity on bond yields is shown for government securities that have the same risk but differ in their liquidity by Amihud and Mendelson (1991), Boudoukh and Whitelaw (1993), Kamara (1994), Elton and Green (1998) and Longstaff (2004). They all find that the bond yield rises as a function of illiquidity.

For corporate bonds, Chen, Lesmond and Wei (2007) find that less liquid bonds (mostly speculative-grade bonds) have higher yield after controlling for default risk and other bond features. deJong and Driessen (2007), Downing, Underwood and Xing (2005) and Lin, Wang and Wu (2011) find that expected return on corporate bonds is increasing in their liquidity risk (*beta*), following the analysis for stocks in Pastor and Stambaugh (2003) and Acharya and Pedersen (2005).

Recent studies, for example, Goldstein, Hotchkiss and Sirri (2005), Edwards, Harris and Piwowar (2007), 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 (starting in 2002). Some of these studies show that liquidity worsened substantially for corporate bonds from the onset of the crisis (3Q/2007) and that this contributed to an enhanced response of bond spreads or returns to liquidity. Chacko (2005) and Chacko, Mahanti, Mallik and Subrahmanyam (2005) measure liquidity of corporate bonds by the turnover of portfolios that contain them, construct a bond return factor based on high and low liquidity bonds and find that its beta coefficient explains the cross-section of bond returns.

Our study differs from the above studies on the effects of liquidity on corporate bonds in that we use liquidity measures that enable the study of long-time series, spanning several economic cycles, allowing more robust inference on expected returns. Goyenko (2006) also studies the cross-market effect of liquidity over a long time-series and finds that stock returns as well as Treasury bond returns are affected by both stock and bond liquidity shocks. In contrast, we study the effect of liquidity *conditional* on the state of the economy and find the conditional effects to be substantial.

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 in sovereign bond returns too, whereby during times of macroeconomic and financial market stress, better-rated sovereign bonds (e.g., the US treasuries) appreciate in value whereas the worse-rated ones decline.

7 Concluding remarks

Our analysis of the effect of conditional liquidity risk on corporate bond returns shows that during economic and financial stress periods, liquidity risk is a significant determinant of bond prices. At the same time, investors exhibit “flight to liquidity,” so that investment-grade bonds appreciate in value relative to the junk-rated bonds during times of stress. Thus, adhering to unconditional or normal-time models entails significant errors for researchers and investors in corporate bonds. For instance, the risk management of corporate bond portfolios should consider not only their liquidity risk, but also the risk that this risk will change. And, if investment grade bonds benefit during stress periods whereas junk bonds are hurt, then our results suggest a diversification of the liquidity risk in broad corporate bond portfolios. Finally, we found that the conditional liquidity risk patterns observed in corporate bond returns are mirrored in stock returns of high and low default-risk firms, and in turn help explain the value premium or the HML factor of Fama and French (1993).

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 4.

Period	1952:2 to 1984:4			1985:1 to 2008:3		
Parameter	Value	Std.Error	t-Value	Value	Std.Error	t-Value
α_1	-0.3403	0.2441	-1.39	0.8738	0.1880	4.65
α_2	1.1727	0.1423	8.24	1.5922	0.2223	7.16
ρ_1	0.0108	0.0895	0.12	-0.2506	0.0992	-2.53
ρ_2	-0.0627	0.0811	-0.77	0.1994	0.0822	2.43
ρ_3	-0.2462	0.0859	-2.87	-0.0532	0.0845	-0.63
ρ_4	-0.2009	0.0867	-2.32	0.0391	0.0802	0.49
σ	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 (in basis points). IG stands for bonds rated BBB and above. Junk stands for bonds rated BB and below. We use the Lehman Brothers Fixed income database for the period January 1973 to December 1996, supplemented with data from the Merrill Fixed Income Securities Database for the period January 1994 to December 2007, giving us a sample period of 1973 to 2007. Included bonds must be in the Lehman/Merrill indices with at least one year to maturity. The average return for each rating group is value weighted by the amount outstanding in that month. Returns are calculated using quoted prices or trades and matrix prices are discarded. Returns for credit rating classes are not available for some months in the sample period, but returns by IG and Junk rating class are available for all months in sample period.

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
IG	420	67.6	127.3	63.0	-428.3	735.1
JUNK	420	97.6	177.9	101.4	-804.0	1069.7

Table 1 Panel B: Summary statistics on bond market factors. This table documents the return on the two factor portfolios DEF, and TERM in basis points, and summary statistics on the Silliq and the Billiq factor. The sample is from January 1973 through December 2007. The default factor (DEF) is the difference between the equally weighted return on all corporate bonds in the database with at least one year to maturity and the average return on one year and thirty year government bond from CRSP. The term factor (TERM) is the difference between the thirty year government bond return and the one month T-bill return from CRSP. Silliq is the innovation in stock market illiquidity measure ILLIQ from Amihud (2002), modified by Acharya and Pedersen (2005), calculated as the residuals of an AR(2) process. Billiq 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
Silliq	420	-0.02161	0.16112	-0.02248	-0.58342	0.65319
Billiq	420	-0.05087	0.43084	-0.02648	-1.55171	2.07333

Table 1 Panel C : Pairwise Spearman correlations of bond market factors. Number in parentheses are p-values for the test that the correlation coefficient equals zero.

	TERM	DEFAULT	Silliq
DEF	-0.529	1	
	(0.00)		
Silliq	0.041	-0.153	1
	(0.40)	(0.00)	
Billiq	-0.057	-0.057	0.086
	(0.25)	(0.25)	(0.08)

Table 2 : Regressions of bond portfolio return on bond market factors. Bond returns for each rating group are in excess of the 30 day T-Bill return. $\beta_T, \beta_D, \beta_{Si}$ *and* β_{Bi} are, respectively, the regression coefficients of TERM, DEF, Silliq and Billiq, respectively, as defined in Table 1, Panel B. Bond returns are calculated as defined in Table 1, Panel A.

Panel A

	Coefficients						t-Stat					
Rating	α	β_T	β_D	β_{Si}	β_{Bi}	Adj-Rsq	α	β_T	β_D	β_{Si}	β_{Bi}	N
AAA	2.68	0.42	0.76	73.70	13.58	0.76	0.83	35.98	22.91	3.69	1.83	415
AA	5.68	0.47	0.81	61.69	1.81	0.79	1.68	38.31	23.27	2.93	0.23	409
A	3.55	0.50	0.90	40.39	-1.66	0.82	1.12	43.67	27.42	2.05	-0.23	415
BBB	3.72	0.47	0.97	17.06	-11.41	0.75	0.97	33.83	24.42	0.72	-1.29	413
BB	14.91	0.38	0.98	-90.15	-57.28	0.51	2.47	17.43	15.85	-2.38	-4.16	405
B	23.61	0.35	0.99	-193.55	-70.07	0.30	2.49	10.25	10.18	-3.26	-3.23	405
CCC & below	84.52	0.21	0.89	-328.70	-63.19	0.11	5.04	3.47	5.33	-3.16	-1.70	369

Panel B

	Ratio to $\sigma_{returns}$ of			
Rating	σ_D	σ_D	σ_{Si}	σ_{Bi}
AAA	99.48%	64.11%	8.83%	4.35%
AA	101.88%	67.96%	7.39%	0.58%
A	104.88%	75.53%	4.84%	0.53%
BBB	98.60%	81.45%	2.04%	3.65%
BB	72.03%	82.30%	10.80%	18.34%
B	50.36%	83.31%	23.18%	22.44%
CCC & below	19.86%	75.35%	39.36%	20.24%

Table 3 Panel A: 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: $r_{IG,t} = \alpha^1_{IG} + \beta^1_{IG,T} TERM_t + \beta^1_{IG,D} DEF_t + \beta^1_{IG,Si} Silliq_t +$
$\beta^1_{IG,Bi} Billiq_t + \epsilon^1_{IG,t}$

Regime 2: $r_{IG,t} = \alpha^2_{IG} + \beta^2_{IG,T} TERM_t + \beta^2_{IG,D} DEF_t + \beta^2_{IG,Si} Silliq_t +$
$\beta^2_{IG,Bi} Billiq_t + \epsilon^2_{IG,t}$

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

Regime 1: $r_{Junk,t} = \alpha^1_{Junk} + \beta^1_{Junk,T} TERM_t + \beta^1_{Junk,D} DEF_t + \beta^1_{Junk,Si} Silliq_t +$
$\beta^1_{Junk,Bi} Billiq_t + \epsilon^1_{Junk,t}$

Regime 2: $r_{Junk,t} = \alpha^2_{Junk} + \beta^2_{Junk,T} TERM_t + \beta^2_{Junk,D} DEF_t + \beta^2_{Junk,Si} Silliq_t +$
$\beta^2_{Junk,Bi} Billiq_t + \epsilon^2_{Junk,t}$

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, χ^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.

	Investment Grade		Junk Grade		Parameters	
Regime 1						
	Coeff	t-stat	Coeff	t-stat		
Constant	2.34	1.36	27.21	4.72	p	0.96
TERM	0.35	44.38	0.28	12.56	q	0.93
DEF	0.37	12.06	1.08	10.07	$\rho_{s_t=1}$	0.10
Silliq	13.95	1.21	-68.89	-2.08	$\rho_{s_t=2}$	-0.40
Billiq	-2.40	-0.49	-14.11	-0.91		
σ_i	24.31		82.96			
Regime 2						
	Investment Grade		Junk Grade			
	Coeff	t-stat	Coeff	t-stat		
Constant	7.21	1.59	22.07	1.44		
TERM	0.52	29.92	0.46	7.56		
DEF	0.97	26.76	1.06	8.78		
Silliq	64.77	3.13	-195.19	-4.31		
Billiq	20.69	2.37	-65.76	-2.37		
σ_i	53.18		188.23			
Table 3 Panel B:						
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	177.18	0.00	11.61	0.00		
Liquidity	10.20	0.01	8.46	0.01		
TERM	89.50	0.00	7.37	0.01		
DEF	167.72	0.00	0.01	0.92		
Silliq	4.44	0.03	5.93	0.01		
Billiq	5.58	0.02	2.53	0.1		
Table 3 Panel C:						
Wald tests for differences in coefficients between IG and Junk						
	Regime 1		Regime 2			
	Chi-Sq	p-value	Chi-Sq	p-value		
TERM & DEF	97.02	0.00	3.79	0.15		
Liquidity	6.42	0.04	35.81	0.00		
TERM	11.00	0.00	0.86	0.36		
DEF	41.81	0.00	0.52	0.47		
Silliq	5.87	0.01	28.22	0.00		
Billiq	0.59	0.44	7.54	0.00		
Log Likelihood	-4676.81					
Sample Period	1973:01 - 2007:12					

Table 3 Panel D: In-Sample accuracy of the Regime Switching Model. This table uses the regime switching model estimated in panel A to obtain estimates of investment grade (IG) and junk grade bond returns in each regime and compares it against the actual realizations. We also estimate an unconditional model over the entire sample (1973-2007) and obtain the predictions. Panels show the regression of the actual bond returns against the predicted bond returns with a test of the slope coefficient = 1.0 and the intercept being 0. $***, **, *$ indicates significance at the 1%, 5%, and 10% levels respectively. Number in parentheses under the coefficients are standard errors.

	Regime 1: Actual returns			
	IG		Junk - Regime 1	
Const.	-.81	-2.09	-.47	7.66
	(1.56)	(1.89)	(5.79)	(5.73)
Predicted - Regime 1 Parameters	1.02***			
	(.02)			
Predicted - Unconditional Parameters		.87***		
		(.02)		
Predicted - Regime 1 Parameters			1.02***	
			(.06)	
Predicted - Unconditional Parameters				.83***
				(.05)
Obs.	276	276	276	276
Adj R^2	.94	.91	.52	.49
F-test if	1.05	66.51	0.13	10.81
Slope = 1.0 (p-value)	(0.307)	(0.000)	(0.722)	(0.001)

	Regime 2: Actual returns			
	IG		Junk	
Const.	1.06	5.16	-3.57	-8.21
	(4.57)	(4.56)	(17.04)	(17.48)
Predicted - Regime 2 Parameters	1.02***			
	(.03)			
Predicted - Unconditional Parameters		1.25***		
		(.04)		
Predicted - Regime 2 Parameters			1.03***	
			(.10)	
Predicted - Unconditional Parameters				1.18***
				(.12)
Obs.	144	144	144	144
$AdjR^2$	.88	.88	.41	.39
F-test if	0.25	40.77	0.11	2.29
Slope = 1.0 (p-value)	(0.620)	(0.000)	(0.742)	(0.132)

Table 4: Explaining the probability of regime 2 (stress regime) with macroeconomic, financial market and bank balance sheet variables

This table presents OLS and logit estimates of the probability of being in regime 2 as a function of macroeconomic and financial market variables. The OLS regression uses as dependent variable the probability of being in regime 2 in any month, that is estimated along with the regime switching model in Table 3. The probability undergoes a logit transformation to map it into the real line, with a constant correction term following Cox (1970, p.33), to accommodate it being bounded between zero and 1. The dependent variable in the logit model is a dummy variable that equals 1 if the probability of being in regime 2 is greater than 70%. Odd (even) numbered specification are OLS (logit) estimations, where the explanatory variables are lagged one period. *NBER Recession* is a dummy variable that equals for NBER recession dates. *SW Index* is the Stock and Watson recession index with positive numbers indicating growth above trend. *Prob(Recession) − Hamilton* is the result of the markov switching model for the quarterly growth rate in U.S. GNP. We use these models to estimate the probability of being in regime 1 (interpreted by Hamilton(1989) as the recession regime) greater than 70%. *Negative Market Return* is a dummy variable that equals one for three consecutive months of negative market return (the CRSP value-weighted return with dividends). *Business Conditions Index*, by based on the framework developed in Aruoba, Diebold and Scotti (2009). The average value of the index is zero, with bigger positive (negative) values indicating better- (worse)-than-average conditions. *Paper Bill Spread* is the difference between the yield on the 3 month non-financial commercial paper rate and the 3 month T-bill secondary market rate. *TED Spread* is the difference between the yield on the 3 month Euro $ deposit rate and the 3 month T-bill secondary market rate, orthogonal to the paper bill spread. *Equity Volatility* is the square root of the monthly average squared daily returns on the CRSP value weighted index with dividends. *EE measure* is the growth in broker dealer balance sheet (relative to households) over the previous 12 months as calculated by Etula (2009). The sample period is January 1973-December 2007. $***, **, *$ indicates significance at the 1%, 5%, and 10% levels respectively. Number in parentheses under the coefficients are standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	-1.92***	-1.03***	-1.11***	-.70***	-2.69***	-1.40***	-1.92***	-1.06***
	(.24)	(.12)	(.22)	(.11)	(.28)	(.16)	(.33)	(.17)
NBER Recession$_{t-1}$	5.88***	2.62***						
	(.50)	(.37)						
SW Index$_{t-1}$			-1.69***	-.76***				
			(.19)	(.13)				
Prob(Recession)- Hamilton$_{t-1}$					4.71***	2.01***		
					(.59)	(.28)		
Negative Market Return$_{t-1}$							3.12***	1.78***
							(.84)	(.48)
Business Conditions Index$_{t-1}$							-1.81***	-.93***
							(.23)	(.17)
Paper Bill Spread$_{t-1}$							.01**	.004**
							(.004)	(.002)
TED Spread$_{t-1}$							.03***	.01***
							(.005)	(.003)
Obs.	419	419	419	419	419	419	419	419
$AdjR^2/PseudoR^2$(%)	18	13	11	8	14	10	23	16

	(9)	(10)	(11)	(12)	(13)	(14)
Const.	-4.57***	-2.50***	-4.69***	-2.54***	-4.75***	-2.62***
	(1.02)	(.40)	(.79)	(.40)	(.79)	(.41)
NBER Recession$_{t-1}$			1.43*	1.20*		
			(.84)	(.61)		
SW Index$_{t-1}$			.12	.06	.006	-.03
			(.33)	(.23)	(.32)	(.23)
Prob(Recession)- Hamilton$_{t-1}$			1.08	1.01**	1.32**	1.21**
			(.67)	(.48)	(.65)	(.47)
Negative Market Return$_{t-1}$			.85	.85	1.11	1.04*
			(.93)	(.59)	(.90)	(.60)
Business Conditions Index$_{t-1}$			-.99***	-.47*	-1.13***	-.60**
			(.35)	(.28)	(.35)	(.28)
Paper Bill Spread$_{t-1}$			.002	-.005	.004	-.002
			(.005)	(.004)	(.005)	(.003)
TED Spread$_{t-1}$			.03***	.01***	.03***	.01***
			(.005)	(.004)	(.005)	(.004)
EE measure$_{previousyear}$	-229.49***	-245.46***	-200.11***	-236.90***	-206.00***	-236.09***
	(76.29)	(56.70)	(58.32)	(46.42)	(57.80)	(46.97)
Equity Volatility$_{t-1}$	93.82***	53.44***	80.39***	49.93***	80.53***	50.01***
	(26.44)	(10.45)	(20.91)	(9.69)	(20.73)	(9.89)
Equity Volatility$_{t-1}$ * EE measure$_{previousyear}$	5099.01***	5009.99***	4248.32***	4011.05***	4364.55***	4029.97***
	(1787.59)	(1336.16)	(1336.11)	(964.58)	(1314.77)	(996.73)
Obs.	419	419	419	419	419	419
$Adj R^2/Pseudo R^2 (\%)$	28	23	44	36	43	35

Table 5: Estimation of the likelihood of regime 2 (stress regime) - out-of-sample tests

This table tests the performance of the probability of regime 2, as predicted by the economic model in Table 4, when compared to the probability of regime 2 obtained from the markov regime switching model of Table 3. First we estimate model (14) of Table 4 using only the data for January 1973-December 1989. Using these estimates, we predict the probability of being in regime 2 for January 1990, then we roll forward every month and repeat the process until we estimate the probability of regime 2 for all months during January 1990-December 2007. We present a logit estimation of the probability of being in regime 2 as as a function of the predicted Prob(Regime 2) as the independent variable. The dependent variable in a dummy variable that equals 1 if the probability of being in regime 2, obtained from the estimates in Table 3, is greater than 70% (following the cutoff level in Hamilton (1989)). We also present a figure that displays the ROC (Receiver Operating Characteristic) curve to assess the accuracy of this logit model to predict regime 2. In the Y-axis we plot the true positive rate, the proportion of actual regime 2 months correctly classified by the model. In the X-axis we plot the false positive rate, the proportion of not regime 2 months that are incorrectly classified as regime 2 months by the model. The diagonal represents random guess. Points above the diagonal indicate good classification results, with the total area under the curve relative to the area of the square measuring the accuracy of the model. $***, **, *$ indicates significance at the 1%, 5%, and 10% levels respectively. Number in parentheses under the coefficients are standard errors.

	Regime 2 (as per Regime Switching Model 1990-2007)
Constant	-1.78***
	(.24)
Predicted Prob(Regime 2)	5.77***
	(.94)
Obs.	216
$PseudoR^2$(%)	27
Area under the ROC curve (%)	88.81

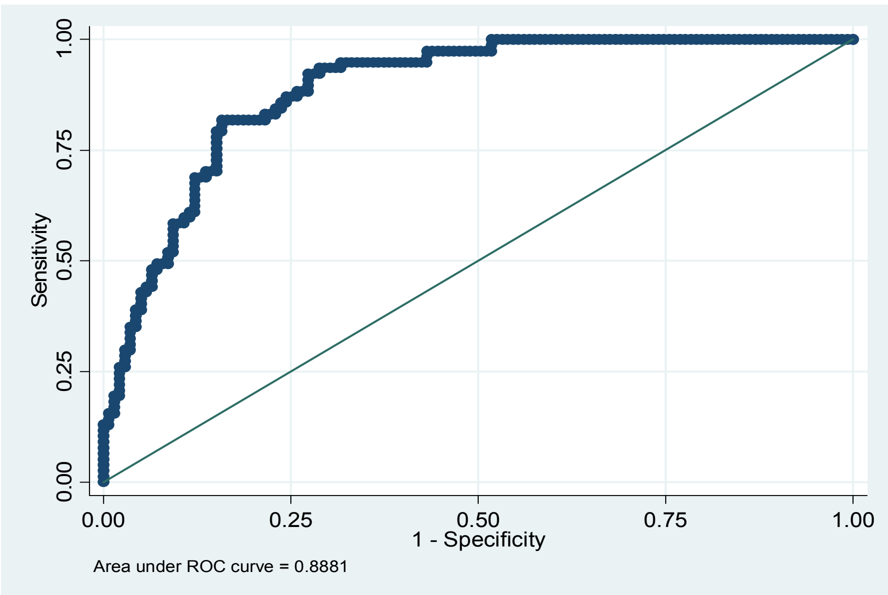

Table 6. Out of Sample Predictions during the Financial Crisis years, 2008-2009.
Panel A shows the actual investment grade and junk grade bond returns (in excess of the 30 day T-bill return) for the years 2008-2009 in basis points. We use the data on iShares investment grade and high yield bond indices to compute the bond returns for these years. The table also presents the estimated probability of regime 2, obtained from specification (14) in Table 4, using the economic time series for December 2007-November 2009 (the predictive economic series are lagged one month). **Panel B** presents the regression of the actual bond returns on the predicted bond returns. The table presents the intercepts and slope coefficients for both investment grade and junk grade bonds, with a test of the slope coefficient = 1.0. To predict bond returns for 2008 and 2009, we proceed as follows: First, we predict the probability as explained in Panel A. Next, we weight the prediction of bond returns itself for 2008-2009 from the regime switching model of table 3 by the respective regime probabilities to obtain the predicted bond returns (in excess of the 30 day T-bill return). Number in parentheses under the coefficients are standard errors.

Panel A Date	IG returns Actual	Junk returns Actual	Predicted Prob(regime 2)	Date	IG returns Actual	Junk returns Actual	Predicted Prob(regime 2)
200801	-139.2	-211.3	0.53	200901	-534.6	-1023.7	0.97
200802	-115.4	80.4	0.97	200902	45.3	188.7	0.91
200803	57.3	316.7	0.85	200903	272.9	1295.6	0.66
200804	-232.7	-60.1	0.98	200904	228.3	280.2	0.002
200805	-185.9	-384.6	0.72	200905	285.0	329.0	0.40
200806	23.0	42.4	0.61	200906	452.1	669.7	0.66
200807	1.9	-102.9	0.81	200907	82.6	-172.4	0.89
200808	-1193.2	-1140.2	0.89	200908	125.6	562.4	0.42
200809	-209.1	-1228.2	0.94	200909	-50.6	-56.0	0.70
200810	325.1	-740.1	1.00	200910	193.2	167.3	0.82
200811	1293.0	1548.1	1.00	200911	-209.2	361.5	0.25
200812	-182.3	-101.6	1.00	200912	152.8	-28.0	0.65

Panel B	Actual IG returns	Actual Junk returns
Constant	4.65	51.15
	(42.93)	(66.82)
Predicted IG returns	0.839***	
	(.098)	
Predicted Junk returns		0.862***
		(.102)
Obs.	24	24
R^2(%)	77	76
F-test if	2.70	1.84
Slope = 1.0 (p-value)	(0.12)	(0.189)

Table 7: Flight to Liquidity Effects

This table presents OLS regressions of returns (or yields) of various bond (assets) portfolios on the probability of being in regime 2 (stress), obtained from the estimation in Table 3, on the four bond market factors described in Table 2 and on the interaction these factors and Prob(regime 2). The returns on Junk and IG (investment grade) are value-weighted averages of the bond portfolios in each group. The estimations in columns (6)-(8) use returns on junk and IG bond portfolios groups by maturity: short-term is up to 4 years, medium term is between 4 and 9 years, and long term is longer than 9 years. Columns (4)-(5) are the yields on 90-day T-bill in excess of the overnight Fed Funds effective rate (to remove policy effects). $***, **, *$ indicates significance at the 1%, 5%, and 10% levels respectively. Number in parentheses under the coefficients are standard errors.

	Junk-IG Return	Junk-IG Return	DEF Return	-(T-Bill Yld - Fed Funds)	-(T-Bill Yld - Fed Funds)	Short Junk-IG	Medium Junk-IG	Long (Junk-IG)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	26.46***	26.02***	6.89	68.09***	48.57***	24.24***	28.43***	24.13**
	(5.96)	(5.99)	(4.34)	(4.15)	(2.82)	(5.03)	(7.68)	(10.23)
Prob(Regime 2)	-2.80	-13.27	-.10		50.71***	-3.50	-27.00	-13.40
	(22.58)	(22.63)	(17.09)		(10.22)	(13.00)	(21.55)	(25.32)
TERM	-.07***	-.08***				-.002	-.18***	-.47***
	(.02)	(.02)				(.02)	(.03)	(.04)
DEF	.84***	.77***		-.07**	-.11**	.55***	.61***	.62***
	(.12)	(.12)		(.03)	(.05)	(.10)	(.15)	(.16)
Silliq		-64.66*	-75.38**	25.02	-10.08	-57.79*	-64.59	-126.09*
		(38.71)	(34.15)	(20.27)	(15.80)	(31.87)	(52.50)	(66.66)
Billiq		-2.00	-29.67**	21.37**	-7.63	-7.38	-5.81	-13.50
		(12.09)	(12.11)	(10.33)	(7.01)	(9.51)	(15.82)	(19.20)
Prob(Regime 2) * TERM	.04	.03				.01	-.06	.15
	(.10)	(.09)				(.05)	(.08)	(.10)
Prob(Regime 2) * DEF	-.66***	-.67***			.05	-.37***	-.71***	-.82***
	(.22)	(.20)			(.06)	(.14)	(.22)	(.24)
Prob(Regime 2) * Silliq		-210.23*	-66.43		58.05	-132.14*	-274.55**	-233.20*
		(111.17)	(119.28)		(43.43)	(76.90)	(118.45)	(137.87)
Prob(Regime 2) * Billiq		-90.79**	35.84		57.14***	-28.04	-76.95*	-104.61**
		(35.79)	(30.64)		(19.89)	(24.93)	(44.93)	(49.71)
Obs.	420	420	420	420	420	356	382	393
$Adj R^2$(%)	11	18	3	3	12	20	30	42

Table 8 Panel A: Estimation of a markov regime switching model for stocks
This table provides the estimates of the following model.

Low Default Risk Stock Returns (in excess of the 30 day T-Bill return):

Regime 1: $r_{Low,t} = \alpha^1_{Low} + \beta^1_{Low,Rm}(R_{m,t} - R_{f,t}) + \beta^1_{Low,T}TERM_t + \beta^1_{Low,D}DEF_t + \beta^1_{Low,Si}Silliq_t + \beta^1_{Low,Bi}Billiq_t + \epsilon^1_{Low,t}$

Regime 2: $r_{Low,t} = \alpha^2_{Low} + \beta^2_{Low,Rm}(R_{m,t} - R_{f,t}) + \beta^2_{Low,T}TERM_t + \beta^2_{Low,D}DEF_t + \beta^2_{Low,Si}Silliq_t + \beta^2_{Low,Bi}Billiq_t + \epsilon^2_{Low,t}$

High Default Risk Stock Returns (in excess of the 30 day T-Bill return):

Regime 1: $r_{High,t} = \alpha^1_{High} + \beta^1_{High,Rm}(R_{m,t} - R_{f,t}) + \beta^1_{High,T}TERM_t + \beta^1_{High,D}DEF_t + \beta^1_{High,Si}Silliq_t + \beta^1_{High,Bi}Billiq_t + \epsilon^1_{High,t}$

Regime 2: $r_{High,t} = \alpha^2_{High} + \beta^2_{High,Rm}(R_{m,t} - R_{f,t}) + \beta^2_{High,T}TERM_t + \beta^2_{High,D}DEF_t + \beta^2_{High,Si}Silliq_t + \beta^2_{High,Bi}Billiq_t + \epsilon^2_{High,t}$

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

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

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, χ^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. Every month we classify stocks in the CRSP database in a 5 X 5 sort based on its modified Z-score (measure of default risk) and monthly equity volatility. Modified Z-score is defined as -4.34-0.08*wcta+0.04*reta-0.1*ebitta-0.22*mvliab+0.06*sata. wcta is the ratio of working capital to total assets (COMPUSTAT item (actq-lctq)/atq). reta is the ratio of retained earnings to total assets (COMPUSTAT item req/atq). ebitta is the ratio of earnings before interest and taxes to total assets (COMPUSTAT item (piq+xintq)/atq). mvliab is the ratio of market value of equity to total liabilities (COMPUSTAT item (prccq * cshoq)/ltq). sata is the ratio of sales to total assets (COMPUSTAT item saleq/atq). For each month, in each volatility quintile, we compute a market capitalization weighted stock return for each Z-score quintile. Low default risk stock returns then is the average of stock returns of the highest Z-score quintile in each volatility quintile. High default risk stock returns then is the average of stock returns of the lowest Z-score quintile in each volatility quintile.

Regime 1						
	Low Default Risk		High Default Risk		Parameters	
	Coeff	t-stat	Coeff	t-stat		
Constant	7.11	0.36	-83.84	-4.41	p	0.98
$R_m - R_f$	120.11	22.60	139.95	27.72	q	0.95
TERM	-0.15	-1.97	-0.23	-2.96		
DEF	0.38	1.14	-0.30	-0.95	$\rho_{s_t=1}$	0.23
Silliq	-170.37	-3.23	-26.75	-0.47	$\rho_{s_t=2}$	-0.17
Billiq	-19.46	-0.40	-3.44	-0.07		
σ_i	301.48		274.67			

Regime 2				
	Low Default Risk		High Default Risk	
	Coeff	t-stat	Coeff	t-stat
Constant	-28.03	-0.62	11.65	0.20
$R_m - R_f$	126.95	11.16	180.27	17.89
TERM	-0.20	-0.68	-0.79	-3.01
DEF	-0.08	-0.18	0.97	26.76
Silliq	-405.33	-6.86	-575.28	-11.74
Billiq	-25.21	-0.39	51.74	0.85
σ_i	581.66		510.51	

Wald tests for differences in coefficients between Regime 1 and Regime 2

	Low Default Risk		High Default Risk	
	Chi-Sq	p-value	Chi-Sq	p-value
$R_m - R_f$	0.28	0.60	12.70	0.00
TERM	0.02	0.88	3.86	0.05
DEF	0.62	0.43	4.66	0.03
Silliq	6.85	0.01	54.33	0.00
Billiq	0.01	0.94	0.66	0.42

Wald tests for differences in coefficients between Low Default Risk and High Default Risk

	Regime 1		Regime 2	
	Chi-Sq	p-value	Chi-Sq	p-value
$R_m - R_f$	9.51	0.00	10.39	0.00
TERM	0.69	0.41	2.25	0.13
DEF	2.40	0.12	5.33	0.02
Silliq	3.26	0.07	3.50	0.06
Billiq	0.15	0.70	0.63	0.43
Log Likelihood	-6103.13			
Sample Period	1973:01 - 2007:12			

Table 9: Explaining the probability of regime 2 (stress regime) with macroeconomic, financial market and bank balance sheet variables

This table presents OLS and logit estimates of the probability of being in regime 2 (for the regime switching model involving stock returns presented in Panel A) as a function of macroeconomic and financial market variables. The OLS regression uses as dependent variable the probability of being in regime 2 in any month, that is estimated along with the regime switching model in Table 8. The probability undergoes a logit transformation to map it into the real line, with a constant correction term following Cox (1970, p.33), to accommodate it being bounded between zero and 1. The dependent variable in the logit model is a dummy variable that equals 1 if the probability of being in regime 2 is greater than 70%. Odd (even) numbered specification are OLS (logit) estimations, where the explanatory variables are lagged one period. $NBER\ Recession$ is a dummy variable that equals for NBER recession dates. $SW\ Index$ is the Stock and Watson recession index with positive numbers indicating growth above trend. $Prob(Recession) - Hamilton$ is the result of the markov switching model for the quarterly growth rate in U.S. GNP. We use these models to estimate the probability of being in regime 1 (interpreted by Hamilton(1989) as the recession regime) greater than 70%. $Negative\ Market\ Return$ is a dummy variable that equals one for three consecutive months of negative market return (the CRSP value-weighted return with dividends). $Business\ Conditions\ Index$, by based on the framework developed in Aruoba, Diebold and Scotti (2009). The average value of the index is zero, with bigger positive (negative) values indicating better- (worse)-than-average conditions. $Paper\ Bill\ Spread$ is the difference between the yield on the 3 month non-financial commercial paper rate and the 3 month T-bill secondary market rate. $TED\ Spread$ is the difference between the yield on the 3 month Euro \$ deposit rate and the 3 month T-bill secondary market rate, orthogonal to the paper bill spread. $Equity\ Volatility$ is the square root of the monthly average squared daily returns on the CRSP value weighted index with dividends. $EE\ measure$ is the growth in broker dealer balance sheet (relative to households) over the previous 12 months as calculated by Etula (2009). The sample period is January 1973-December 2007. $***, **, *$ indicates significance at the 1%, 5%, and 10% levels respectively. Number in parentheses under the coefficients are standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	-2.79***	-1.25***	-2.60***	-1.24***	-3.74***	-1.76***	-2.28***	-1.09***
	(.23)	(.13)	(.21)	(.12)	(.26)	(.18)	(.28)	(.17)
NBER Recession$_{t-1}$	1.41**	.35						
	(.62)	(.31)						
SW Index$_{t-1}$			-1.01***	-.39***				
			(.22)	(.11)				
Prob(Recession)- Hamilton$_{t-1}$					3.36***	1.42***		
					(.57)	(.30)		
Negative Market Return$_{t-1}$							3.39***	1.43***
							(.94)	(.52)
Business Conditions Index$_{t-1}$							-1.31***	-.64***
							(.23)	(.18)
Paper Bill Spread$_{t-1}$							-.01***	-.008**
							(.004)	(.003)
TED Spread$_{t-1}$							-.04***	-.02***
							(.005)	(.005)
Obs.	419	419	419	419	419	419	419	419
$AdjR^2/PseudoR^2(\%)$	1	0.3	5	3	9	5	18	8

	(9)	(10)	(11)	(12)	(13)	(14)
Const.	-6.18***	-3.10***	-5.25***	-2.80***	-5.22***	-2.72***
	(.85)	(.57)	(.86)	(.54)	(.86)	(.59)
NBER Recession$_{t-1}$			-.74	-1.24*		
			(.78)	(.75)		
SW Index$_{t-1}$			-.50*	-.34	-.44	-.23
			(.30)	(.26)	(.30)	(.25)
Prob(Recession)- Hamilton$_{t-1}$			1.13*	.48	1.01*	.30
			(.62)	(.43)	(.61)	(.44)
Negative Market Return$_{t-1}$			1.74*	1.07	1.60	.84
			(1.04)	(.70)	(1.01)	(.70)
Business Conditions Index$_{t-1}$			-.35	-.27	-.28	-.12
			(.33)	(.31)	(.31)	(.27)
Paper Bill Spread$_{t-1}$			-.02***	-.007*	-.02***	-.01***
			(.004)	(.004)	(.004)	(.004)
TED Spread$_{t-1}$			-.03***	-.01**	-.03***	-.01**
			(.005)	(.005)	(.005)	(.005)
EE measure$_{previousyear}$	-63.83	-40.43	-109.89*	-65.99	-106.84*	-59.83
	(65.84)	(55.75)	(64.59)	(49.87)	(64.35)	(53.05)
Equity Volatility$_{t-1}$	80.02***	39.18***	76.24***	41.18***	76.17***	40.83***
	(22.64)	(13.59)	(23.67)	(13.76)	(23.73)	(14.85)
Equity Volatility$_{t-1}$ * EE measure$_{previousyear}$	3379.56**	1934.17	3024.38**	1947.27*	2964.27**	1798.85
	(1512.44)	(1287.17)	(1497.33)	(1164.09)	(1497.20)	(1229.37)
Obs.	419	419	419	419	419	419
Adj $R^2/PseudoR^2$(%)	26	18	38	24	37	23

Table 10: The predictive power of the probability of regime 2 (stress regime) for stocks and bonds
We denote for convenience $Prob(Regime\ 2)_t^{Bond}$, obtained from the estimation of model for bond returns in table 3, by $BP2$ and $Prob(Regime\ 2)_t^{Stock}$, obtained from model for stock returns in table 8, by $SP2$. $\Delta\ SP2$ and $\Delta\ BP2$ are the first differences. The series are monthly. The estimation employs the Newey-West method (with four lags). Number in parentheses under the coefficients are standard errors.

	$\Delta\ BP2_t$	$\Delta\ SP2_t$
	(1)	(2)
Const.	-.004	-.002
	(.006)	(.005)
$\Delta\ SP2_t$	.03	
	(.04)	
$\Delta\ SP2_t^2$	.06	
	(.05)	
$\Delta\ SP2_{t-1}$	.28**	
	(.13)	
$\Delta\ SP2_{t-1}^2$	.55**	
	(.27)	
$\Delta\ BP2_t$		.04***
		(.02)
$\Delta\ BP2_t^2$		.04**
		(.02)
$\Delta\ BP2_{t-1}$		-.009
		(.01)
$\Delta\ BP2_{t-1}^2$		-.008
		(.02)
Obs.	418	418
R^2(%)	4	0.5

Table 11: The effect on Fama and French's (1993) HML of SP2 and of HML_{def}, high-minus-low default stock return

The dependent variable is Fama and French's (1993) HML factor, the return differential of stocks with high and low book-to-market ratio. We denote for convenience $Prob(Regime\ 2)_t^{Stock}$, obtained from the estimation of model for stock returns in table 8, by $SP2$. HML_{def} is the return differential between portfolios of high and low default risk, which are used in Table 8. The classification by default risk employs the modified Z-score of stocks. The estimation employs the Newey-West method (with one lag). The series are monthly from January 1973 to December 2007. Number in parentheses under the coefficients are standard errors.

	(1)	(2)	(3)	(4)
Const.	.62***	.55***	.24**	.27**
	(.14)	(.14)	(.11)	(.11)
$(R_M - R_f)$	-.31***	-.23***	-.19***	
	(.04)	(.04)	(.04)	
$(R_M - R_f) * SP2$		-.22**	-.09	
		(.11)	(.07)	
SP2		.15	.55*	
		(.47)	(.31)	
HML_{def}			-.34***	-.38***
			(.03)	(.02)
Obs.	420	420	420	420
$R^2(\%)$	21	23	59	48

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

The top panel (Fig.1.) plots in basis points the returns on corporate bonds by credit rating classes. See definitions in Table 1. The middle (Fig.2.) and bottom (Fig.3.) present the four bond market factors that we use: TERM (term premium), DEF (default premium), Silliq (innovations on stock illiquidity) and Billiq (innovations on bond illiquidity). See definitions in Table 2. NBER recession dates are also shown.

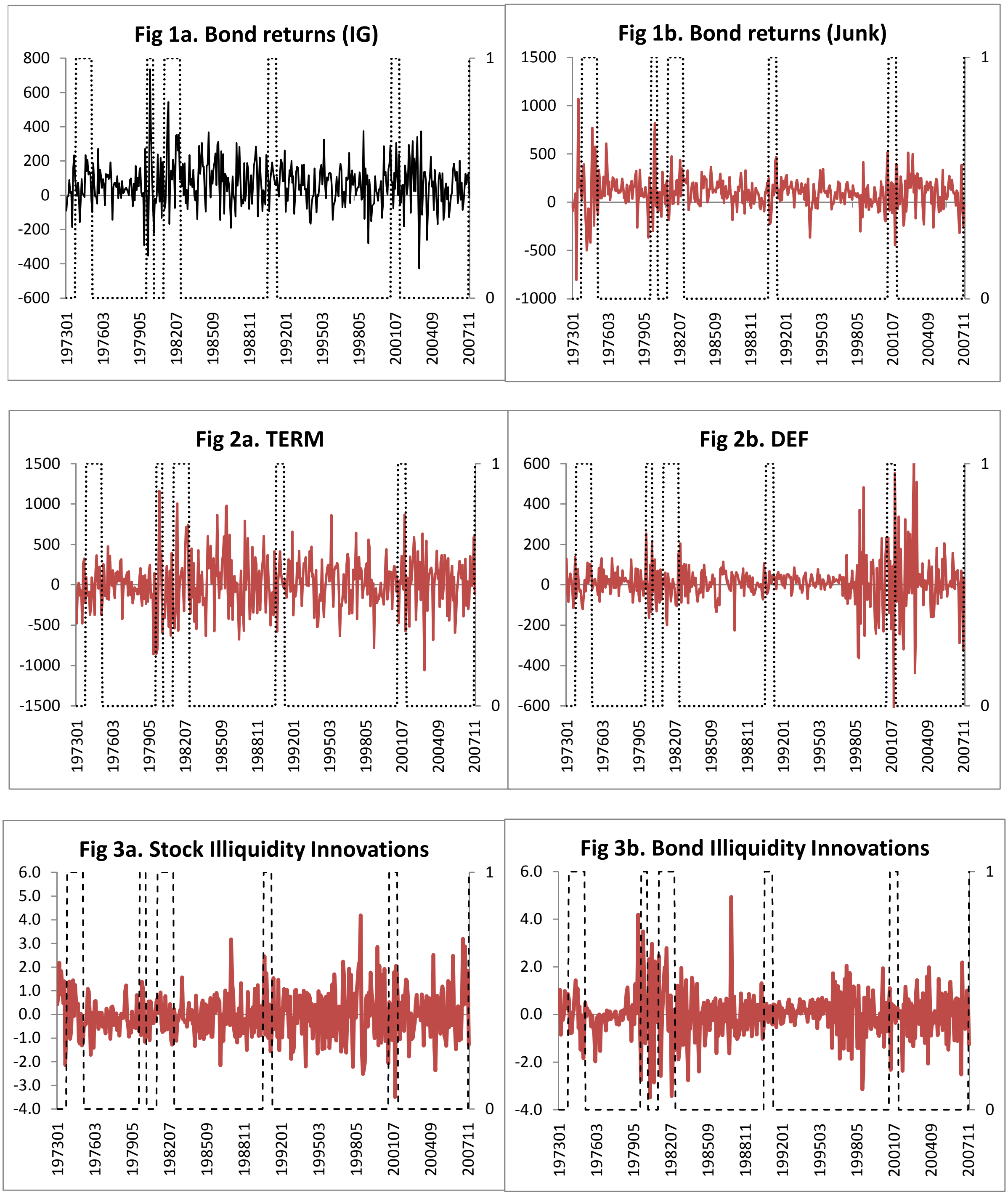

Fig.4. Probability of high illiquidity stress regime estimated from a regime switching model. For details on the regime switching model refer Table 3. We use the model to estimate the probability of being in regime 2 interpreted as the high illiquidity stress regime. NBER recession dates are shown.

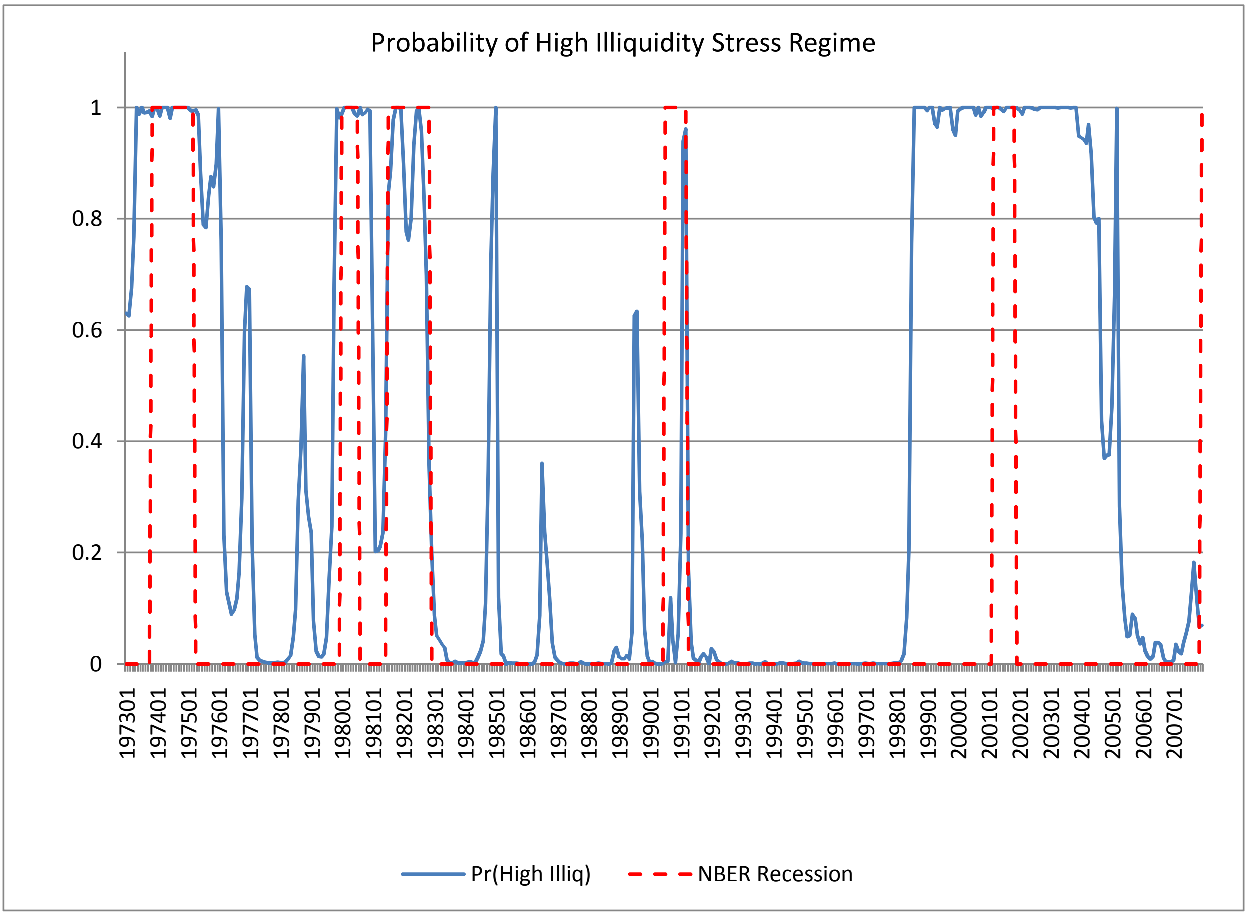

Fig.5. Regime Switching Model - Out of Sample Predictions during the Financial Crisis year of 2008 and year 2009.

This figure presents the regression of the actual bond returns against the predicted bond returns for the period 2008-2009. Actual returns are obtained from data on iShares investment grade and high yield bond indices. The returns used are in excess of the 30 day T-bill return. To predict bond returns for 2008 and 2009, we proceed as follows: First, we predict the probability of regime 2 as explained in Table 6, Panel A. Next, we weight the prediction of bond returns itself for 2008-2009 from the regime switching model of table 3 by the respective regime probabilities to obtain the predicted bond returns (in excess of the 30 day T-bill return).