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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 to 2007. A decline in liquidity of stocks or Treasury bonds produces conflicting effects: Prices of investment-grade bonds rise while prices of speculative grade bonds fall substantially. This effect is regime-switching in nature and holds when the state of the economy is in a "stress" regime. The likelihood of being in such a regime can be predicted by macroeconomic and financial market variables that are associated with adverse economic conditions. Our model can predict the out-of-sample bond returns for the stress years 2008-2009. These effects are robust to controlling for other systematic risks (term and default). Our findings suggest the existence of time-varying liquidity risk of corporate bond returns and episodes of flight to liquidity.

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1 Introduction

Liquidity shocks affect asset prices because asset liquidity affects expected returns of both stocks and bonds (Amihud and Mendelson, 1986, 1991). Because asset illiquidity is persistent (highly autoregressive), an unexpected rise in illiquidity raises expected illiquidity. Consequently, investors require higher expected returns, which makes asset prices fall if the rise in illiquidity does not have an appreciable positive effect on assets' cashflow. This generates a negative *liquidity beta* of assets, i.e., a negative relationship between illiquidity shocks and asset realized returns, which is documented for stocks by Amihud (2002), for bonds by deJong and Driessen (2004) and Liu, Wang and Wu (2010), and is employed by Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Sadka (2006) in analyzing the effect of liquidity risk on the expected return of stocks. However, these papers examine the *unconditional* effect of liquidity risk, that is, averaged over time. In particular, this body of research has by and large not yet examined the casual observation that the impact of liquidity shocks on asset prices is highly *conditional*, significantly stronger in bad economic times. Acharya and Pedersen (2005) note that significant illiquidity episodes in the stock market were preceded by significant macroeconomic or market-wide shocks during the period 1964-1999,[1] and Watanabe and Watanabe (2008) suggest a regime-switching pattern of response of stock returns to liquidity, but they do not relate it to macroeconomic conditions.[2]

This paper shows that the response of corporate bond prices to liquidity shocks of stocks and Treasury bonds varies over time in a systematic way, switching between two regimes which we call "normal" and "stress." We first identify the two regimes statistically as those when the effects of liquidity shocks, as well as those of term and default risk, differ between the two regimes, employing Hamilton's (1989) methodology. Our important result is that the two regimes can be predicted by macroeconomic and financial variables. We find that the periods of stress are associated with adverse macroeconomic conditions, such as recessed economic activity, and adverse financial market conditions such as negative stock market returns and heightened volatility. Finally, employing these predictions of being in the normal or the stress regime, we provide out-of-sample prediction of corporate bond returns for the years 2008-2009. Regressions of monthly realized returns on predicted returns produce R^2 of 74% and 77% for junk and investment grade bonds, respectively. The coefficients on predicted return are close to one and the intercepts are close to zero (differences are

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

[2] See also Fujimoto (2003)

statistically insignificant). 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).[3]

Our analysis reveals a pattern of "flight to liquidity" only in the stress regime, wherein investors prefer to hold more liquid assets such as investment grade (IG) bonds rather than the less liquid non-investment-grade ("junk") bonds. We find that the response of bond returns to liquidity shocks in the stress regime is quite the opposite for IG and junk bonds. Whereas junk bond returns respond negatively to illiquidity shocks in stress, IG bond returns respond positively. In the normal regime, there is no significant difference in response to liquidity shocks between IG and junk bonds. This pattern is robust to controlling for maturity and default risk.

2 Summary of our model and results

We estimate a two-regime switching regression model, which we later show to pertain to normal time or to time of economic stress. There are two regression models, one for IG bonds and one for junk bonds in which we regress monthly bond returns (in excess of the 30-day T-bill rate) on innovations in two illiquidity indexes of stock and bonds, and on two bond return factors which capture the excess return on maturity-related and default-related portfolios of bonds. These factors have been used in earlier studies.

We obtain that for junk-bond returns, the betas of the two illiquidity factors are statistically insignificant in normal times, but they become highly negative and significant in the stress regime. In contrast, the default factor beta does not change appreciably in the stress regime, and the coefficient of the maturity factors changes very little. A one standard deviation in either of the liquidity factors in time of stress produces between one tenth to one fifth of a standard deviation of bond returns, compared to only one twentieth (or less) of a standard deviation shock in returns during normal times. In other words, during stress times, the effect of liquidity risk on junk bond returns rises by a factor of two to four times compared to normal times.

The response of IG bond prices to innovations in illiquidity is quite the opposite of that of junk bonds. In the stress regime, IG bond prices respond *positively* to innovations in

[3]In another out-of-sample test we start with the second half of the sample and progressively estimate the best econometric fit using macroeconomic and financial-market variables that explain the model-implied probability of being in the stress regime until the previous month, and use it to predict the probability of being in the stress regime this month. The prediction has significant power with an accuracy of over 89%.

illiquidity, particularly to innovations in bond illiquidity. This is in addition to the rise in the IG bond returns betas on both maturity and default factors in the stress regime. In stress time, these two betas become insignificantly different from the maturity and default betas of junk bonds, while in normal time, the maturity and default betas are significantly lower for IG bonds than they are for junk bonds.

We propose an economic meaning for our statistically-driven regimes by showing how they relate to macroeconomic and financial market conditions. The regime-switching estimation provides a model-implied probability of a given month being in the normal regime or the stress regime. We then regress the probability of being in the stress regime on lagged macroeconomic and financial market variables: the NBER recession dummy, Stock and Watson index of leading economic indicators, the probability of being in a recession based on Hamilton's model, a dummy variable for negative market return, and the business conditions index (Arouba, Diebold and Scotti, 2009), the yield spread between commercial paper and Treasury bills, the yield spread between the Eurodollar and Treasury bill rate, stock market volatility, and the interaction of stock market volatility and past year's growth in broker-dealer balance-sheets (as measured by Etula (2009)). The estimated coefficients of these variables indicate that the stress regime is associated with adverse macroeconomic and financial market conditions, that is, *economic stress*. For example, the likelihood of being in the stress regime is positively related to the NBER recession dummy variable, with the relationship being very highly significant. The best econometric fit using all of the indicators explains about 42% of the time-series variation in model-implied probability of being in the stress regime.

The varying response of bond prices to illiquidity innovations in periods of stress indicates that investors become less willing to hold junk bonds relative to IG bonds which are known to be more liquid (see Chen et al., 2007). Another interpretation is that illiquidity shocks foretell heightened investor risk-aversion to extreme events or rare disasters (Rietz, 1988 and Barro, 2006) which induces an aversion to riskier assets such as junk bonds. Yet another explanation is the volatility feedback explanation of Campbell and Hentschel (1992) that increases in aggregate volatility necessitate a reduction in investor holdings of risky assets, which reduces their contemporaneous returns. To distinguish between these explanations, we examine the return on junk bonds relative to IG bonds and find that greater default risk in the stress regime is associated with more negative junk-IG differential return, consistent with a flight to quality. However, adding interaction effects of the stress regime with liquidity innovations on both bonds and stocks to explain the junk-IG differential return increases the explanatory power of the model by 70%, underscoring the importance of the flight to liquidity effects. We find that greater illiquidity of stocks and treasury bonds significantly lowers the junk-IG differential return in the stress regime, consistent with a flight to liquidity effect. We further find that the reaction of the junk-IG bond returns to illiquidity shocks in times of stress is monotonically increasing with bond maturity, being more negative for longer-term bonds. This is in addition to the effect of default risk in stress time being more negative as a function of bond maturity. Again, we find that the flight to liquidity in times of stress is distinct from the flight to liquidity. The default premium itself, while being affected by liquidity shocks, does not have excess response to liquidity shocks in time of stress. This shows that the effects of liquidity shocks on the junk-IG bond differential in time of stress is not associated with the effect of default risk.

In a further test that differentiates between flight to liquidity and to safety, we study how the negative of the prices of T-bills responds to liquidity shocks in time of stress (relative to the Federal Funds rate). Treasury bills are high “quality” assets, being an investment that is both safe and highly liquid. We find that the T-bill price rises during the stress regime, and it rises furthermore if there is also a rise then in bond illiquidity. This reflects flight to liquidity when, in times of stress, similar to the pattern observed for investment grade bonds. In contrast, treasury bill returns do not react to increase in default risk in the stress regime. This is also consistent with a stronger flight-to-liquidity phenomenon than a flight-to-quality one.

The rest of the paper proceeds as follows. Section 3 describes the data we employ. Sections 4 and 5 present results for our unconditional and conditional liquidity risk tests, respectively. Section 5 also reports results of the out-of-sample tests. Section 6 discusses additional related literature. Section 7 concludes.

3 Data

Our bond data are extracted from the Lehman Brothers Fixed Income Database distributed by Warga (1998) and supplemented by the Merrill Lynch corporate bond index database used by Schaefer and Strebulaev (2008). We follow closely the data extraction methodology outlined by Bharath and Shumway (2008) for the Warga (1998) database. The Warga (1998) database contains monthly price, accrued interest, and return data on all corporate and government bonds 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

[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.

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 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. For the latter we average the 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.

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

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

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.[7] The bond illiquidity measure is the equally weighted quoted bid-ask spread on on-the-run short maturity treasuries.[8] The innovations in both of these indexes are the residuals from an autoregressive model with 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 -0.059 and with Silliq it is -0.141). 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.

[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(2) model for stock illiquidity is estimated beginning in July 1962 and the bond AR(2) model is estimated beginning in November 1967, because longer period provides better estimation of the process.

4 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.

4.1 Methodology and results

First, we estimate the following time-series specification:

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

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 $j \in \{$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 is 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 ratings (except for the CCC group), consistent with worse credit quality.

Of primary interest to this paper, the liquidity risk loadings 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, the effect of bond liquidity risk is positive for all IG bonds and the effect of stock liquidity risk 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 higher-quality bonds which are more liquid. 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 76% and 83%), but it deteriorates substantially for below-BBB bonds (adj-R^2 falls from 51% for BBB to 11% for CCC and below).[10]

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 3% to 8% 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.

5 Conditional liquidity risk

As discussed in the introduction, most of the current academic literature has focused on unconditional liquidity risk as we also analyzed thus far. However, as noted by Acharya and Pedersen (2005), liquidity risk may matter more in periods of illiquidity crises and for less liquid securities. From an economic perspective, there are sound reasons to believe that the effect of liquidity risk is episodically high while being muted most of the time. This could be because investor aversion to liquidity risk may exhibit time-variation. Of particular relevance to corporate bonds, financial institutions are usually the marginal price-setters in these markets. In normal times, such institutions are far away from their funding or capital

[10]de Jong and Driessen (2005) estimate a model with two liquidity risk factors as we do, but while we employ two bond-market-based control variables, TERM and DEF, as in Fama and French (1993), they use the S&P 500 index return as control. When we add the S&P 500 index return to our model, it is insignificant (see also Gebhradt et al (2005)). Their results on the effects of liquidity risks are somewhat different. First, all but one of the liquidity coefficients for both stocks and bonds are negative, while in our analysis the coefficients switch from positive to negative as we decline in the bond rating. Thus our results suggest the phenomenon of flight to liquidity, which they do not find. Second, while their liquidity factors coefficients are generally more negative for lower-rated bonds, the pattern is not as close to being monotonic as ours.

constraints. But in times of adverse liquidity shock, such as decline in funding liquidity or a decline in asset values which erodes their equity capital and makes their position more constrained (e.g., due to higher margin requirements), they may need to improve the liquidity of their balance sheets. Then, financial institutions may reflect an aversion to holding less liquid corporate bonds in lieu of more liquid ones.[11] This is more likely to happen during recessions or financial crises.

Thus, we expect the following effect. In episodes of adverse economic conditions, a rise in market illiquidity raises the expected illiquidity in the market, which in turn raises the market illiquidity premium. This leads to a decline in all bond prices. However, in such periods investors substitute from less liquid to more liquid bonds, which means that the effect of liquidity risk is exacerbated for less liquid bonds, while liquid bonds become more desirable.[12] This makes the effect of liquidity risk on bonds become conditional on the state of the economy and financial markets. We test this hypothesis as follows.

5.1 Regime-switching model of bond betas

We perform a regime-switching analysis of corporate bond betas on various risk factors, separately for investment grade and junk bonds. In essence, we let the data tell us whether there is a set of times when betas are substantially 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 supportive of there being a regime switch in the nature of liquidity risk of stock returns.

5.1.1 Methodology

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

[11]For theoretical motivation of the effects of these kinds of asset, volatility or funding shocks and the induced de-leveraging and market liquidity effects, see Gromb and Vayanos (2002), Acharya and Viswanathan (2007), He and Krishnamurthy (2008, 2009) and Brunnermeier and Pedersen (2009).

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

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.

5.1.2 Results

The results in Table 3 Panel A show a clear pattern of two regimes in IG and junk bond with varying betas, especially for the two liquidity variables. In Regime 1, the two liquidity betas are statistically insignificant for both IG and 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 sixfold and that of Billiq rises over 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.

Panel B of Table 3 shows that the change in the liquidity betas is particularly significant for IG bonds and for the Billiq beta, in which case the beta changes from being negative and insignificant in regime 1 to positive and significant in regime 2. The change in regime 2 is also more pronounced for the beta of Silliq of junk bonds, where it changes from insignificant -37.06 in regime 1 to a significant -220.33 in regime 2. Tests of the difference in coefficients between IG and junk bonds in the two regimes are presented in Panel C of Table 3. The tests show that in regime 1 there is no significant difference between the liquidity betas of IG and junk bonds. However, in regime 2, both liquidity betas are significantly different between IG and junk bonds. 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 does not change (even slightly declines) for junk bonds. This is striking because junk bonds are more vulnerable to default risk, and given that the liquidity betas become much more negative for junk bonds in regime 2. 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.

Finally, Panel C also shows that in regime 2, the difference between the TERM coefficients for IG and junk bonds is significant only in regime 1 but not in regime 2.

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 different directions, being positive for IG bonds and negative for junk bonds. This 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. We have 4 regressions: for each of the two regimes, we do a regression for IG and junk bonds. For all four regressions, under the conditional model, the slope coefficient is practically 1 (as one would expect trivially) and the intercept is zero, as expected. By comparison, when using predicted returns from the unconditional model, the slope coefficients of actual returns on predicted returns is away from 1. In regime 1, the coefficients of the predicted returns are below 1.0 for both IG and junk bond returns, with the difference from 1.0 being highly significant. This means that the unconditional model underestimates high returns and overestimates low returns. For regime 2, it is the opposite. The predicted returns from the unconditional model underestimate actual returns for low returns and overestimate them for high returns. This is evident from the slope coefficient being greater than 1.0, which is significant for IG bonds. 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 6% and that of Billiq rises from 0.7% to 7%. For junk bonds, the rise in the effect of Silliq is from 5% to 16% and for Billiq the rise is from 4% to 13%.

5.1.3 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 investigate this important issue below. We undertake an *economic identification* of the regimes, using macroeconomic variables and confirm that regime 2 is indeed associated with economic 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 in 70's (picking up the oil-price shock of mid 70's and the high interest-rate regime of late 70's), early 80's (again, during the high interest-rate environment) and the financial market stress and the ensuring recession during the period 1998-2003. The regime-switching model also appears to pick up stress in 1989 leading up to the NBER recession of 1990 and 1991, and does not identify mid 90's as a stress period. However, 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, the 9/11/2001 attack and their aftermath 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).

[13] Detailed results are available upon request.

[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 being in state 1 at time t-1, and the product of the transition probability from state 2 to state 2 with the probability 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 tth observation. See Hamilton, 1994 for details.

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 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) 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 return.

(iii) Business Condition Index, due to Aruoba-Diebold-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, whereas more negative values indicate worse-than-average conditions.

(iv) 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).

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

(vi) Paper-Bill spread: the 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 data is constructed from the U.S. Flow of Funds data which is available only at quarterly frequency for the full sample period. In our prediction, we use the growth rates based on past one year's data. A rise in EE measure indicates expectations of good business conditions.

(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 use 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 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 precisely during volatile times, greater broker inventory growth in the past is 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.

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 10% to 27%. 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

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

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 junk bonds (Table 3) has a sound economic foundation. 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.

5.2 Out of sample regime prediction during 1990-2007

The economic foundations of the stress regime 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 the stress regime (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 model (14) of 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 till 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 (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 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 (model in Table 3 panel A), is above 70%.

ENTER TABLE 5

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 89.01%. 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.

5.3 Out of sample predictions during the financial crisis of 2008

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 of 2008 and 2009 being in the stress regime, using the macroeconomic and financial market variables included in model (14) in Table 6 and the coefficients of that estimation model to predict the 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. 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 by estimating a regression model of the actual bond return as function of the predicted bond return. In such a regression with an ideal predictor, we expect the intercept to be zero and the slope coefficient to be 1. Panel B of Table 6 documents the results of these regressions. The regression has a reasonably good fit of 77% for the IG bonds and 74% for the junk grade bonds. Further, the slope coefficients on the predicted returns are statistically indistinguishable from 1.0 (at the 0.05 level) for both IG and junk bond grades, and the constant is not different from zero in both these regressions. 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

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

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, (corresponding to all months except January and June in the year 2008) as well as in regime 1, corresponding to six months in the year 2009.

5.4 Flight to liquidity

One interpretation of our overall results is that consistent with the literature on asset pricing with frictions (as discussed in the introduction), stressed macroeconomic and financial conditions make investors more risk-averse to illiquidity shocks and they respond by switching from junk bonds to investment-grade bonds which are known to be more liquid (see Chen et al., 2007).[17] An alternative explanation is that the rise in the effect of liquidity shocks on bond prices proxies 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 $Adj\ R^2 = 10\%$ to $Adj\ R^2 = 17\%$. 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

[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 commonly employed proxy of illiquidity, is of the order of 6-10 percent for investment grade bonds and 20-40 percent for junk bonds.

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 the common part of the illiquidity effect on IG and junk bond returns. This is observed in Table 7, column (3), where both Billiq and Silliq effects are statistically significant. However, *Adj* R^2 is quite low, only 2%. Also, 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, 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 is immune to default risk and thus reflects 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 rise and their yield will fall. There are two points to note. First, the inclusion of the liquidity variables increases the explanatory power of the model more than five times, from *Adj* R^2 of 2% to *Adj* R^2 of 11%. This attests to the importance of liquidity risk in determining the T-bill return. 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.

5.5 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 the yield. Also, long-term corporate bonds have lower liquidity than do short-term bonds (again, see Chen et al. (2007)), hence 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

[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.

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 coefficient of Billiq is generally negative, because a rise in bond illiquidity lowers junk bond prices and raises IG bond prices. This effect 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 -16.95 for short-term bonds to a significant -83.21 for medium-term bonds and a significant -109.36 for long-term bonds. Similarly, the coefficient of Silliq is negative but insignificant, but it becomes more negative and highly significant when considering the interaction term Prob(Regime 2)*Silliq. This coefficient falls monotonically from -134.65 for short-term bonds to -266.33 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.

6 Related literature

Our study is in line with the now burgeoning literature on asset pricing with frictions, showing that risk premiums on assets fluctuate due to capital and financing conditions of financial intermediaries. He and Krishnamurthy (2008, 2009) argue that adverse macroeconomic conditions lower intermediary capital which in turn raises conditional volatility in asset markets and causes risk-free interest rates to fall. Their asset-pricing model leads to a small unconditional liquidity effect which can, however, turn into a large conditional liquidity effect. These theoretical implications are consistent with our findings for corporate bond returns. Acharya and Viswanathan (2007) show that when aggregate shock is sufficiently severe, highly leveraged intermediaries are forced to liquidate their risky positions and asset markets can clear only at "cash-in-the-market" prices (Shleifer and Vishny, 1992, Allen and Gale, 1994, 1998). Such prices depend on the financing capacity of low leverage intermediaries, which is also limited in adverse conditions due to potentially severe agency problems in raising external finance. Brunnermeier and Pedersen (2009) show that funding illiquidity adversely affects market liquidity when there are margin constraints that rise in times of higher volatility, and Garleanu and Pedersen (2009) argue that an asset's required return depends not only on its beta on traditional risk factors but also on the asset's exposure to conditions that cause some of its marginal investors to face rising margin constraints (and on the share of such constrained investors). Finally, He and Xiong (2009) and Morris and Shin (2009) argue that liquidity risk should amplify credit risk rather than affecting asset prices independently. Our result that junk bonds are adversely affected by liquidity risk factors in times of aggregate stress is consistent with these results. In addition, we present results on IG bond prices responding positively to illiquidity shocks which captures a flight to liquidity, which some these models do not consider.

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

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

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

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

More closely related to our work, Longstaff, Mithal and Neis (2005) show that the basis between corporate bond spreads and credit default swap premia is explained by fluctuations in treasury liquidity. de Jong and Driessen (2005) follow Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) by estimating two liquidity *betas* of bond returns with respect to stock and bond liquidity shocks, using Amihud's (2002) *ILLIQ* for stock illiquidity and quoted bid-ask spreads on long-term U.S. Treasury bonds, as well as the beta on the S&P 500 index. They find that bonds with lower rating and longer maturities have more negative liquidity betas, implying that these bonds have higher illiquidity premium. The de Jong and Driessen study is the closest to our unconditional analysis (Table 2), but they have a much shorter time-series and they do not study conditional behavior of liquidity betas as we do. Lin, Wang and Wu (2010) is similar to de Jong and Driessen in studying the unconditional cross section of expected corporate bond returns. They use the TRACE bond data set from 2002-2007 and find that liquidity risk is priced. Sangvinatsos (2009) studies the importance of corporate bonds in overall investor portfolio and documents that there exist flight-to-liquidity premia in investment grade bonds but not in high yield bonds.

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

7 Conclusion

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

We acknowledge that a relevant factor for corporate bond returns is also the liquidity specific to corporate bond market, since this liquidity may not necessarily be spanned by treasury bond and stock market illiquidity. First, the corporate bond market trading tends to be highly institutional in nature and shocks relevant for these institutions may need to be identified.[19] Acharya, Schaefer and Zhang's (2007) study of the excess co-movement in credit default swaps around the General Motors (GM) and Ford downgrade of May 2005

[19]Chacko (2005) and Chacko, Mahanti, Mallik and Subrahmanyam (2005) employ a liquidity measure based on turnover of portfolios containing corporate bonds and find that a return factor based on high and low liquidity bonds explains the cross-section of bond returns.

shows that the co-movement was linked to the risk faced by corporate-bond market-makers when there were sudden liquidations of GM and Ford bonds. Further investigation along these lines seems to be a fruitful avenue for research.

Second, some recent studies[20] use newly available daily trading data on corporate bonds from TRACE platform in the United States. The recent papers also 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. These effects are entirely consistent with the conditional liquidity effects we uncover for corporate bonds over the period 1973 to 2008, even though due to data limitations we did not explicitly employ any corporate bond liquidity measure.

Finally, recent work (Panyanukul, 2009) has also found liquidity risk to be a priced factor in explaining sovereign bond returns, especially during the period 2007 to 2009. We conjecture that there is a strong conditional component to liquidity effects 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.

[20]See 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)

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	0.00570	0.17289	-0.00962	-0.61920	0.61809
Billiq	420	0.00694	0.43048	0.03318	-1.48166	2.12169

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	0.007	-0.141	1
	(0.88)	(0.00)	
Billiq	-0.055	-0.059	0.086
	(0.26)	(0.23)	(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, 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_i	β_{bi}	N
AAA	-0.11	0.42	0.76	65.33	14.01	0.76	-0.03	35.98	22.85	3.50	1.89	415
AA	3.93	0.47	0.80	48.16	2.41	0.78	1.17	38.19	23.13	2.45	0.31	409
A	2.49	0.50	0.90	42.34	-1.32	0.83	0.79	43.75	27.48	2.31	-0.18	415
BBB	3.86	0.47	0.97	24.11	-11.52	0.75	1.02	33.85	24.46	1.08	-1.30	413
BB	20.81	0.38	0.97	-83.39	-56.89	0.51	3.49	17.31	15.79	-2.38	-4.13	405
B	32.91	0.35	0.99	-156.93	-70.41	0.30	3.50	10.13	10.16	-2.83	-3.24	405
CCC & below	97.72	0.20	0.89	-308.25	-65.06	0.11	5.89	3.36	5.29	-3.18	-1.75	369

Panel B

	Ratio to $\sigma_{returns}$ of			
Rating	σ_t	σ_d	σ_{si}	σ_{bi}
AAA	99.80%	64.12%	8.40%	4.48%
AA	102.07%	67.83%	6.19%	0.77%
A	105.11%	75.68%	5.44%	0.42%
BBB	98.75%	81.64%	3.10%	3.69%
BB	71.69%	82.15%	10.72%	18.20%
B	50.01%	83.58%	20.17%	22.53%
CCC & below	19.25%	74.84%	39.61%	20.82%

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.

Regime 1						
	Investment Grade		Junk Grade		Parameters	
	Coeff	t-stat	Coeff	t-stat		
Constant	2.12	1.09	29.81	5.17	p	0.95
TERM	0.35	49.10	0.28	12.48	q	0.93
DEF	0.37	11.94	1.10	9.81	$\rho_{s_t=1}$	0.11
Silliq	14.39	1.40	-37.06	-1.28	$\rho_{s_t=2}$	-0.39
Billiq	-1.97	-0.42	-12.32	-0.82		
σ_i	23.87		81.96			
Regime 2						
	Investment Grade		Junk Grade			
	Coeff	t-stat	Coeff	t-stat		
Constant	4.06	0.91	32.60	2.18		
TERM	0.52	30.09	0.44	7.41		
DEF	0.96	26.76	1.04	8.63		
Silliq	51.24	2.50	-220.33	-4.11		
Billiq	22.49	2.60	-65.63	-2.47		
σ_i	53.51		186.94			
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	179.35	0.00	10.67	0.00		
Liquidity	9.05	0.01	10.53	0.01		
TERM	91.08	0.00	6.01	0.01		
DEF	170.13	0.00	0.10	0.75		
Silliq	2.47	0.12	8.90	0.00		
Billiq	6.19	0.01	2.97	0.08		
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	94.79	0.00	4.22	0.12		
Liquidity	3.37	0.19	28.85	0.00		
TERM	9.78	0.00	1.29	0.26		
DEF	40.25	0.00	0.34	0.56		
Silliq	3.08	0.08	24.04	0.00		
Billiq	0.49	0.49	8.37	0.00		
Log Likelihood	-4677.78					
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.

	Actual returns			
	IG - Regime 1		Junk - Regime 1	
Const.	-.34	-1.68	-.39	8.01
	(1.46)	(1.81)	(5.98)	(5.96)
Predicted - Regime 1 Parameters	1.00***			
	(.02)			
Predicted - Unconditional Parameters		.86***		
		(.02)		
Predicted - Regime 1 Parameters			.99***	
			(.06)	
Predicted - Unconditional Parameters				.80***
				(.05)
Obs.	269	269	269	269
$Adj R^2$	.94	.91	.48	.45
F-test if	0.00	78.05	0.01	13.10
Slope = 1.0 (p-value)	(0.977)	(0.000)	(0.935)	(0.000)

	Actual returns			
	IG - Regime 2		Junk - Regime 2	
Const.	1.07	4.95	.36	-4.81
	(4.54)	(4.54)	(16.11)	(16.50)
Predicted - Regime 2 Parameters	1.00***			
	(.03)			
Predicted - Unconditional Parameters		1.24***		
		(.04)		
Predicted - Regime 2 Parameters			1.00***	
			(.09)	
Predicted - Unconditional Parameters				1.17***
				(.11)
Obs.	151	151	151	151
$Adj R^2$	.88	.88	.43	.42
F-test if	0.02	40.12	0.00	2.31
Slope = 1.0 (p-value)	(0.877)	(0.000)	(0.966)	(0.131)

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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	.32***	-.94***	.39***	-.62***	.25***	-1.27***	.30***	-1.03***
	(.02)	(.12)	(.02)	(.11)	(.03)	(.15)	(.03)	(.17)
NBER Recession$_{t-1}$	5.78***	2.66***						
	(.49)	(.38)						
SW Index$_{t-1}$			-1.67***	-.76***				
			(.18)	(.13)				
Prob(Recession)- Hamilton$_{t-1}$					4.63***	1.90***		
					(.58)	(.28)		
Negative Market Return$_{t-1}$							3.07***	1.64***
							(.82)	(.48)
Business Conditions Index$_{t-1}$							-1.79***	-.96***
							(.23)	(.18)
Paper-Bill Spread$_{t-1}$							.01**	.005**
							(.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	9	22	16

	(9)	(10)	(11)	(12)	(13)	(14)
Const.	-4.45***	-2.28***	-4.57***	-2.27***	-4.63***	-2.35***
	(1.01)	(.39)	(.79)	(.38)	(.78)	(.39)
NBER Recession$_{t-1}$			1.38*	1.10*		
			(.82)	(.60)		
SW Index$_{t-1}$			.12	.06	.009	-.02
			(.33)	(.23)	(.32)	(.24)
Prob(Recession)- Hamilton$_{t-1}$			.98	.64	1.21*	.83*
			(.66)	(.47)	(.65)	(.47)
Negative Market Return$_{t-1}$			.86	.77	1.11	.95*
			(.92)	(.56)	(.88)	(.57)
Business Conditions Index$_{t-1}$			-1.01***	-.63**	-1.14***	-.74**
			(.35)	(.29)	(.35)	(.29)
Paper-Bill Spread$_{t-1}$			.002	-.002	.005	-.0003
			(.005)	(.003)	(.004)	(.003)
TED Spread$_{t-1}$			.03***	.01***	.03***	.01***
			(.005)	(.004)	(.005)	(.004)
EE measure$_{previousyear}$	-219.35***	-219.36***	-189.98***	-202.39***	-195.68***	-202.48***
	(75.64)	(53.61)	(58.01)	(41.53)	(57.49)	(41.97)
Equity Volatility$_{t-1}$	92.34***	49.39***	79.02***	44.39***	79.16***	44.51***
	(26.19)	(10.15)	(20.75)	(9.01)	(20.57)	(9.17)
Equity Volatility$_{t-1}$ * EE measure$_{previousyear}$	4985.20***	4505.29***	4163.96***	3509.64***	4276.37***	3535.87***
	(1771.89)	(1276.12)	(1326.92)	(880.58)	(1306.43)	(906.29)
Obs.	419	419	419	419	419	419
$AdjR^2/PseudoR^2(\%)$	27	21	42	33	42	33

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.

	Regime 2 (as per Regime Switching Model 1990-2007)
Constant	-1.93***
	(.25)
Predicted Prob(Regime 2)	5.90***
	(.94)
Obs.	216
$PseudoR^2$(%)	27
Area under the ROC curve (%)	89.01

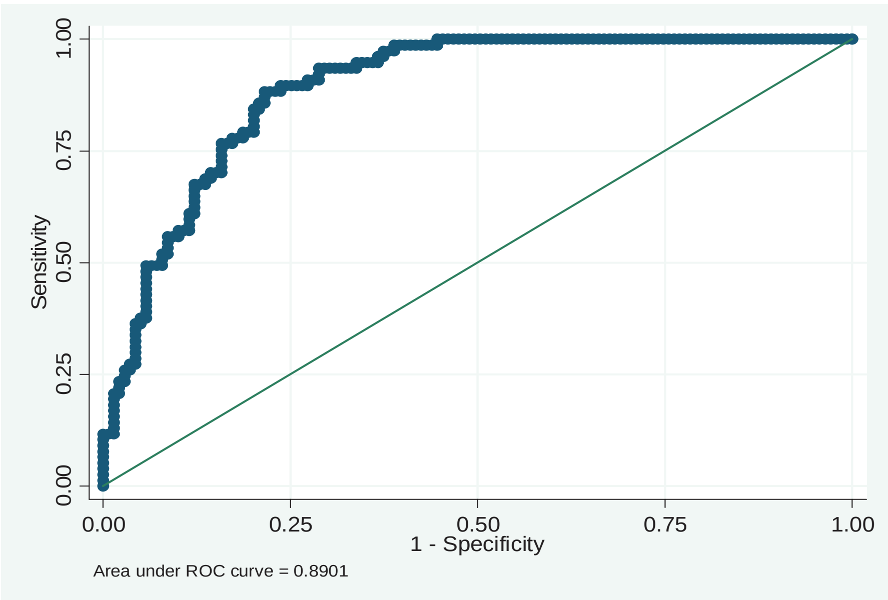

Table 6. Out of Sample Predictions during the Financial Crisis years, 2008-2009.
Panel A shows the actual investment grade and junk grade bond returns (in excess of the 30 day T-bill return) for the years 2008-2009 in basis points. We use the data on iShares investment grade and high yield bond indices 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	IG returns	Junk returns	Predicted		IG returns	Junk returns	Predicted
Date	Actual	Actual	Prob(regime 2)	Date	Actual	Actual	Prob(regime 2)
200801	-139.2	-211.3	0.60	200901	-534.6	-1023.7	0.98
200802	-115.4	80.4	0.95	200902	45.3	188.7	0.93
200803	57.3	316.7	0.83	200903	272.9	1295.6	0.71
200804	-232.7	-60.1	0.97	200904	228.3	280.2	0.01
200805	-185.9	-384.6	0.71	200905	285.0	329.0	0.42
200806	23.0	42.4	0.59	200906	452.1	669.7	0.63
200807	1.9	-102.9	0.78	200907	82.6	-172.4	0.83
200808	-1193.2	-1140.2	0.87	200908	125.6	562.4	0.38
200809	-209.1	-1228.2	0.95	200909	-50.6	-56.0	0.62
200810	325.1	-740.1	1.00	200910	193.2	167.3	0.74
200811	1293.0	1548.1	1.00	200911	-209.2	361.5	0.24
200812	-182.3	-101.6	1.00	200912	152.8	-28.0	0.57

Panel B	Actual IG returns	Actual Junk returns
Constant	8.778	50.340
	(43.341)	(69.828)
Predicted IG returns	0.832***	
	(.098)	
Predicted Junk returns		0.855***
		(.107)
Obs.	24	24
R^2(%)	77	74
F-test if	2.92	1.81
Slope = 1.0 (p-value)	(0.102)	(0.192)

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.

	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.	26.91***	27.53***	10.20**	66.34***	48.53***	25.99***	30.89***	25.60**
	(5.92)	(5.94)	(4.08)	(3.83)	(2.80)	(4.92)	(7.65)	(10.10)
Prob(Regime 2)	-3.82	.21	1.26		47.69***	.52	-9.66	15.67
	(22.45)	(21.55)	(15.20)		(9.60)	(15.86)	(22.26)	(29.19)
TERM	-.07***	-.07***				.002	-.18***	-.47***
	(.02)	(.02)				(.02)	(.03)	(.04)
DEF	.84***	.80***		-.07**	-.11**	.56***	.65***	.64***
	(.12)	(.12)		(.03)	(.05)	(.10)	(.16)	(.17)
Silliq		-29.44	-55.98*	.39	-13.62	-25.55	-14.08	-79.67
		(35.49)	(33.36)	(18.55)	(14.31)	(28.15)	(49.83)	(61.81)
Billiq		-.27	-29.12**	23.80**	-7.80	-6.34	-4.36	-12.17
		(11.98)	(12.09)	(10.40)	(7.07)	(9.87)	(15.92)	(19.20)
Prob(Regime 2) * TERM	.04	.006				.03	-.07	.06
	(.09)	(.09)				(.05)	(.08)	(.12)
Prob(Regime 2) * DEF	-.67***	-.73***			.04	-.37**	-.76***	-.93***
	(.22)	(.20)			(.06)	(.15)	(.22)	(.25)
Prob(Regime 2) * Silliq		-263.73**	-78.40		7.59	-134.65	-246.62**	-266.33*
		(103.32)	(110.22)		(41.54)	(88.63)	(120.16)	(146.69)
Prob(Regime 2) * Billiq		-94.09***	33.06		63.27***	-16.95	-83.21*	-109.36**
		(36.27)	(30.54)		(19.94)	(26.41)	(45.29)	(53.01)
Obs.	420	420	420	420	420	420	420	420
$Adj R^2$(%)	10	17	2	2	11	9	23	36

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.

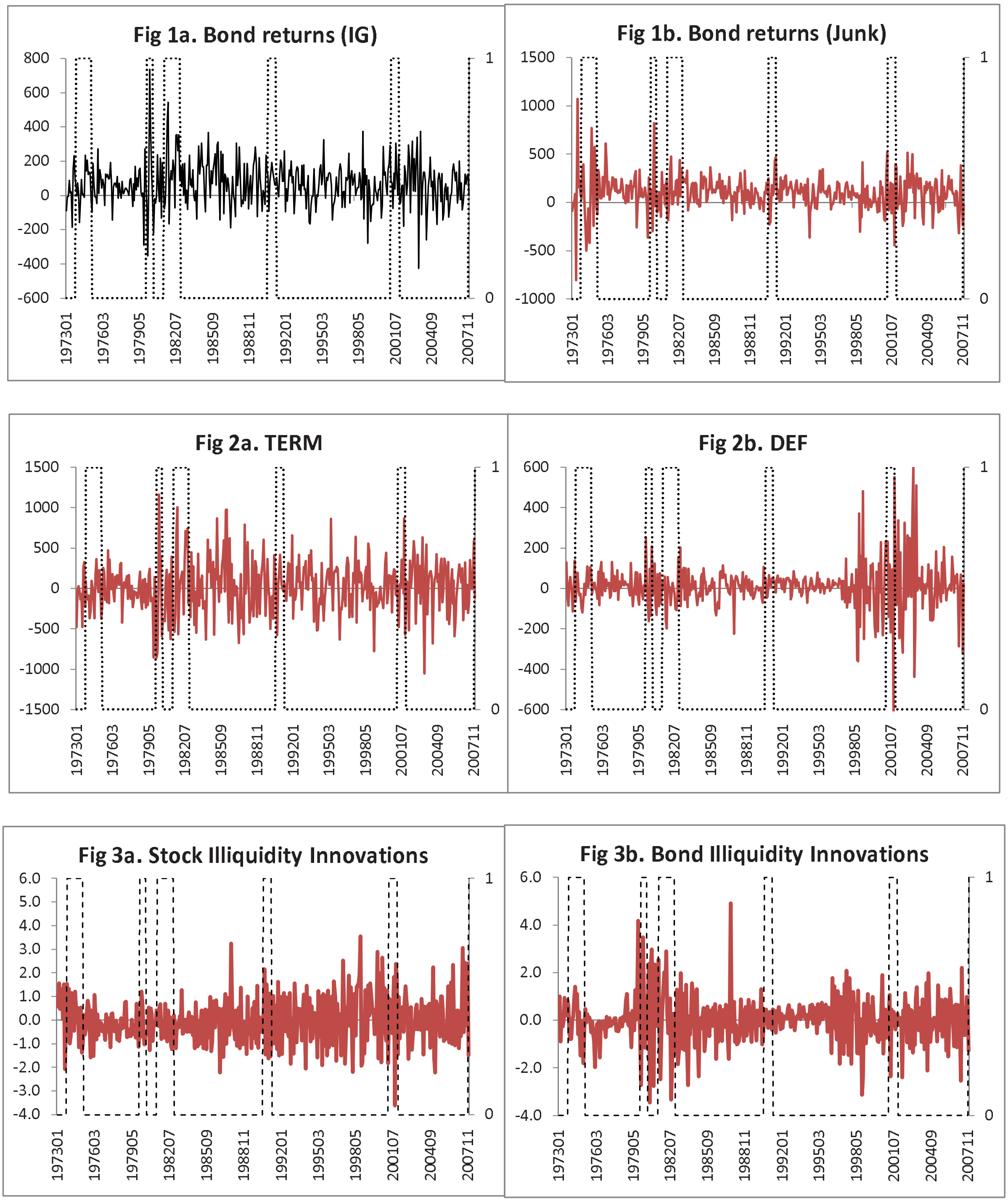

Fig.4. Probability of high illiquidity stress regime estimated from a regime switching model.
For details on the regime switching model refer Table 3. We use the model to estimate the probability of being in regime 2 interpreted as the high illiquidity stress regime. NBER recession dates are shown.

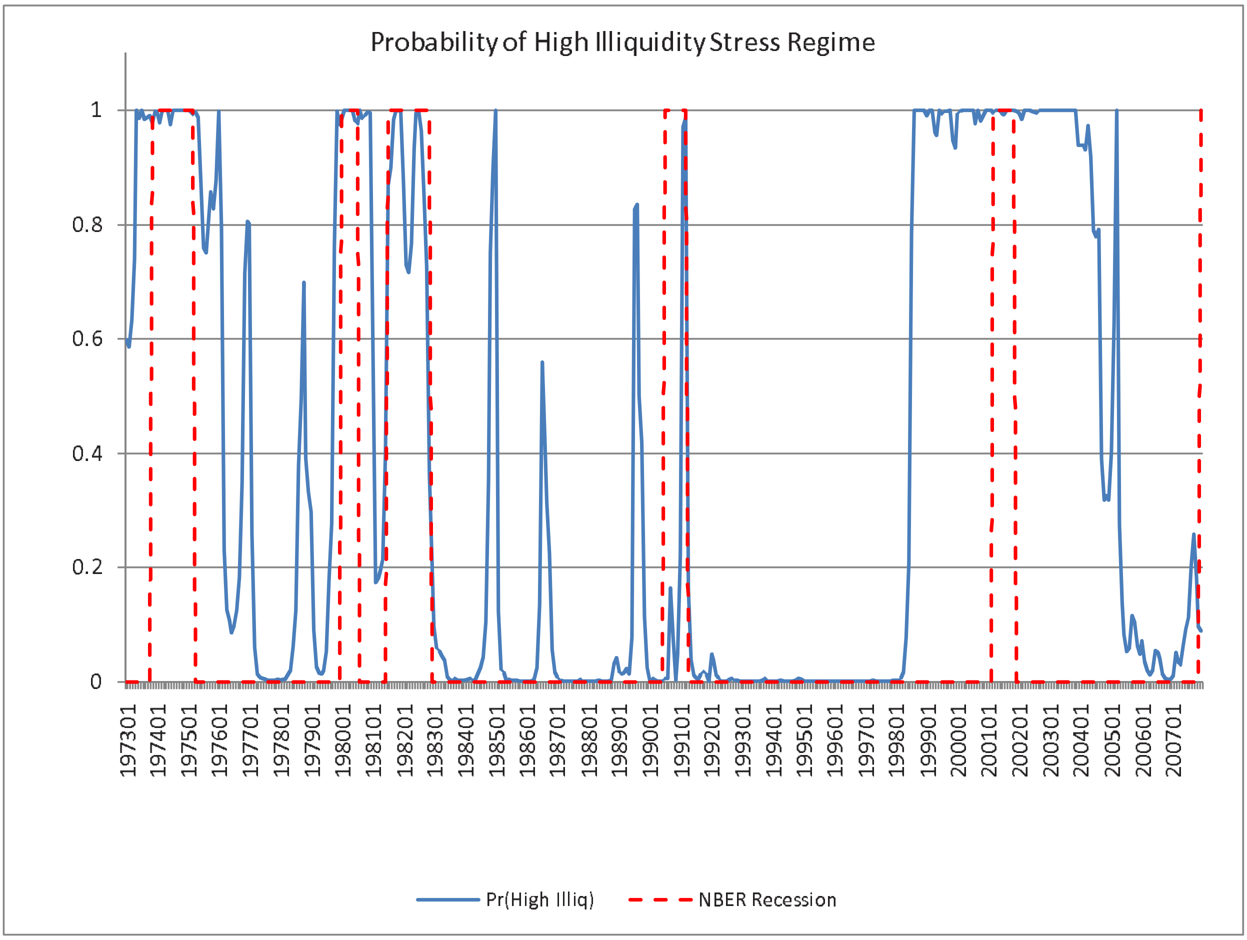

Fig.5. Regime Switching Model - Out of Sample Predictions during the Financial Crisis year of 2008 and year 2009.

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).