# Liquidity Risk and Momentum Spillover from Stocks to Bonds

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The literature has documented evidence of a pronounced momentum effect in stock returns (Jegadeesh and Titman [1993, 2001]; Chan, Jegadeesh, and Lakonishok [1996]). Stocks that have performed the best in the recent past continue to do well in the future. This return pattern appears to be robust across different markets (Rouwenhorst [1998]; Griffin, Ji, and Martin [2003]; Chui, Titman, and Wei [2010]; Fama and French [2011]; Menkhoff et al. [2012]). The magnitude of momentum profits in economic terms is difficult to justify by standard risk-based theory. Therefore, alternative explanations have been proposed to explain the momentum anomaly by such behavioral factors as underreaction to information or investor overconfidence (Hong and Stein [1999]; Chui, Titman, and Wei [2010]), transaction costs (Korajczyk and Sadka [2004]), or limits to arbitrage (Chabot, Ghysels, and Jagannathan [2009]).[1]

An issue that naturally arises is whether the momentum effect exists in other asset classes. Empirical research in this area has provided mixed results. On the one hand, a number of studies have shown evidence of momentum in various assets, such as currencies (Kho [1996]; LeBaron, [1999]; Okunev and White [2003]; Menkhoff et al. [2012]), commodities (Gorton, Hayashi, and Rouwenhorst [2008]), and government bonds (Asness, Moskowitz, and Pedersen [2013]). On the other, Gebhardt, Hvidkjaer, and Swaminathan [2005] find no evidence of momentum in returns of investment-grade corporate bonds.[2] Instead, they find a significant momentum spillover effect from equities to investment-grade corporate bonds of the same firm. Firms that have had high equity returns in the recent past earn high bond returns in the following year. This spillover effect appears to be robust to various risk and liquidity controls.

The phenomenon of momentum spillover from stocks to bonds presents a challenge to asset pricing theory. Given the sheer size of the corporate bond market, it is important to understand what causes the spillover effect. A possible explanation is that the corporate bond market is less informationally efficient than the equity market. Corporate bonds are less liquid than stocks. To the extent that informed traders prefer to trade in a more liquid market, new information could be impounded faster in the stock market than in the bond market. This argument, however, is not consistent with the empirical finding that the corporate bond market is as informationally efficient as the stock market (see Hotchkiss and Ronen [2002]).

Another possible explanation for the equity momentum spillover is underreaction of prices to fundamental news. Underreaction could be a potential problem for corporate bond pricing if bond investors do not pay sufficient attention to the fundamental information. Nevertheless, this explanation is not convincing either, as Hotchkiss and Ronen [2002] show that corporate bonds prices react to fundamental information in the same way as stock prices.

The equity momentum spillover presents a profitable opportunity, but bond market traders may be prevented from exploiting this effect due to transaction costs. Gebhardt et al. [2005] examine the effect of transaction costs for corporate bonds and find that trading costs weaken the profitability of momentum spillover strategies. This finding is consistent with the evidence that transaction costs reduce momentum returns in the stock and current markets (Korajczyk and Sadka [2004]; Menkhoff et al. [2012]).

That the profitability of momentum strategies hinges on transaction costs raises the issue of whether returns on these strategies can be related to temporal variations of liquidity documented in the literature (Chordia, Roll, and Subrahmanyam [2000]). Momentum returns are relatively short-lived, and implementing momentum strategies requires high portfolio turnover. As a result, values of these portfolios are susceptible to fluctuations in liquidity. If liquidity shocks induce systematic risk, momentum returns can be regarded as compensation for investors bearing liquidity risk if returns of momentum portfolios are sensitive to unanticipated shocks to aggregate liquidity.

Several important studies on the equity market momentum have explored this possibility. For example, Pastor and Stambaugh [2003] show that liquidity risk explains about half of the equity momentum return. Using a refined measure of the liquidity factor, Sadka [2006] finds that liquidity risk can explain between 40% and 80% of the cross-sectional variation in expected momentum returns. Both studies show that stock winners have a high liquidity beta. Studies in hedge fund portfolios have also shown that liquidity risk is an important determinant in the cross-section of hedge-fund returns (Sadka [2010]; Teo [2011]). Funds that significantly load on the liquidity risk factor subsequently have higher returns than low-loading funds. These findings highlight the importance of liquidity risk in explaining the subsequent returns of momentum portfolios and hedge funds.

In light of the literature on liquidity risk in the equity return momentum, this article explores the role of liquidity risk in the momentum spillover from stocks to corporate bonds. The liquidity risk we investigate is not the risk that liquidity will be low when investors need to trade but is instead the risk that the bond's value will drop when marketwide liquidity worsens. More specifically, the risk examined in this study is determined by how a bond's return fluctuates in association with a state variable and not by how the bond's liquidity fluctuates.

Our approach thus contrasts with that of Gebhart et al. [2005], who study the effects of transaction costs or the level of the bond's liquidity on momentum spillover return. The fact that the level of liquidity can affect the momentum return is not surprising, because investors incur transaction costs. Our article contributes to the literature by focusing on a new dimension of the liquidity effect that has not yet been explored in the studies of momentum return spillovers.

Stocks and bonds are financial claims whose payoff depends on the assets of the same firm, and so they share common characteristics. Firms that have high stock liquidity risk would therefore tend to have high bond liquidity risk. For example, firms with high credit risk may have assets whose values are sensitive to aggregate liquidity shocks, and as a consequence, both stock and bond returns have high exposures to liquidity risk.

This argument is supported by the literature. Avramov et al. [2007] find that stock momentum profits are positively related to the credit risk of firms. Sadka [2006] finds that firms with high stock momentum returns have a high stock liquidity beta. Lin, Wang, and Wu [2011] find that high credit risk firms have a high bond liquidity beta. Together, these studies suggest that high credit risk firms have both a high stock and bond liquidity beta and also high stock momentum. Their findings suggest that liquidity risk can potentially be important in explaining the momentum returns. This article extends these studies by examining whether firms with high momentum spillover from stocks to bonds will have a high bond liquidity beta.

A number of studies have documented that liquidity is an important factor in corporate bond pricing. Bao, Pan, and Wang [2011] find a strong relation between illiquidity and bond prices. Lin, Wang, and Wu [2011] find that liquidity risk explains a significant portion of the cross-sectional variation in expected corporate bond returns. Friewald, Jankowitsch, and Subrahmanyam [2012] and Dick-Nielsen, Feldhutter, and Lando [2012] show that liquidity is an important pricing factor and that its effects are more pronounced for speculative-grade bonds. While these studies examine the pricing of liquidity risk in the cross-section of bond returns as a whole, we focus on the role of liquidity risk in momentum spillover returns. Given that liquidity is important in corporate bond pricing, it is natural to ask whether the momentum spillover profits are related to liquidity risk.

Our objective is to investigate whether liquidity risk can explain the equity momentum spillover anomaly in the corporate bond market. We examine how much of the momentum spillover return can be attributed to compensation for exposures to liquidity shocks. Using a long-span transaction dataset, we assess the effect of liquidity risk on returns of momentum portfolios based on efficient asset pricing tests. An advantage of this dataset is that it contains a large number of speculative-grade bonds, which permits us to examine whether the equity momentum spillover also exists in noninvestment-grade bonds, an issue unexplored in the literature.[3]

We find that momentum spillover bond portfolio returns are sensitive to liquidity shocks. There is strong evidence that liquidity risk is positively related to bond returns of equity momentum spillover strategies. This positive effect remains significant economically and statistically, even after controlling for the effects of behavioral factors, idiosyncratic liquidity, and bond characteristics. On average, the liquidity beta explains about 40% of the momentum spillover profit for investment-grade bonds and 55% for speculative-grade bonds over a 16-year sample period. Results suggest that a significant portion of bond returns associated with the equity momentum spillover can be construed as compensation for investors bearing liquidity risk in trading this anomaly.

This article contributes to the current literature of momentum and corporate bond pricing in several aspects. First, we show that the same equity-based liquidity risk factor that explains equity momentum (see Pastor and Stambaugh [2003]; Sadka [2006]) also explains the momentum spillover from stocks to corporate bonds. Second, we document a more pronounced effect of equity momentum spillover for speculative-grade bonds than for investment-grade bonds. Third, the momentum spillover effect depends on liquidity and credit quality of corporate bonds. Bonds with lower liquidity experience a greater momentum spillover effect. Furthermore, the liquidity factor interacts with the credit risk factor. The effect of liquidity on the equity momentum spillover is stronger for bonds with a lower rating.

Last, the liquidity factors used in this study capture the effects of important liquidity events. The liquidity of low-grade bonds, which have the highest momentum spillover returns overall, dries up faster than that of other bonds during a financial crisis. Results show that liquidity risk of high momentum spillover portfolios manifests itself in the trading activities of the underlying bonds. In anticipation of costly liquidation in a low-liquidity environment, investors require higher expected returns for low-grade bonds. This explains why portfolios of speculative-grade bonds have both stronger momentum spillover and a higher liquidity beta.

The remainder of our article is organized as follows. After we describe the data and liquidity measures used in the empirical tests, we examine the effect of the momentum spillover by using both portfolio and regression analyses and report results for the whole sample as well as subsamples by rating. We then investigate the pricing of liquidity risk with momentum spillover portfolios and estimate the proportion of the spillover return explained by the liquidity risk factor. Additional tests are performed to check the robustness of results to alternative explanations. Next, we examine the importance of liquidity risk and momentum profits in different economic regimes, and the final section summarizes our main findings and concludes the article.

## DATA

The bond data are assembled from several sources: the Trading Reporting and Compliance Engine (TRACE) and National Association of Insurance Commissioners (NAIC) databases, Datastream, the Lehman Brothers Fixed Income Database (LBFI), and the Fixed Investment Securities Database (FISD). The data for stocks listed on the NYSE, AMEX, and Nasdaq are obtained from the Center for Research in Security Prices (CRSP) database. Intraday and monthly return data are both used in our empirical analysis.

The TRACE database contains price, time, and size of transactions for publicly traded over-the-counter (OTC) corporate bonds. The TRACE database was established in July 2002 to improve transparency in the corporate bond market. Through several phases of expansion, TRACE has covered transactions of most publicly traded bonds since October 1, 2004.[4] The only trades not included in the TRACE database are those executed through exchanges, most of which occur on the NYSE's Automated Bond System. As less than 5% of all bonds are listed on the NYSE, the current TRACE database contains the vast majority of corporate bond trades in the U.S. fixed-income market.

The NAIC database covers all transactions of publicly traded corporate bonds, beginning in January 1994, by life and property and casualty insurance companies and health maintenance organizations (HMOs). The Flow of Funds Accounts of the United States published by the Federal Reserve Bank show that about one-third of outstanding corporate bonds are held by insurance companies. Several studies have used the NAIC data and note that it covers bond transactions that are adequately representative of the corporate bond market (see Campbell and Taksler [2003]; Krishnan, Ritchken, and Thomson [2005]; Cai, Helwege, and Warga [2007]).

The LBFI database contains month-end bid prices, accrued interest, and characteristics of corporate bonds. Lehman Brothers constructs its closely watched corporate bond indexes from the prices in the LBFI database. We choose only corporate bonds with dealer quotes, as Sarig and Warga [1989] show that matrix prices are problematic. Daily prices for corporate bonds are obtained from Datastream International, which uses Merrill Lynch as the data source. The bond price is an average price across all market makers for the bond. We construct monthly returns by using these prices observed at month-end. We select only U.S. dollar–denominated bonds and exclude those bonds with variable coupons. The LBFI and Datastream datasets are two major sources of monthly bond returns in the early period of our sample.

The FISD database includes issuance information for all fixed-income securities that have a CUSIP and those likely to receive one soon. It contains issue- and issuer-specific information, such as coupon rate, maturity, issue amount, provisions, and credit ratings for corporate bonds maturing in 1990 or later.

TRACE and NAIC provide transaction data of corporate bonds. Transaction data are used for constructing liquidity factors to estimate liquidity risk. In addition, volume and frequency of transactions are important information for ascertaining the effect of liquidity on momentum returns. The TRACE database covers corporate bond transactions for a relatively short horizon. Also, initially TRACE includes only a small subset of investment-grade corporate bonds, which are not representative of the whole market. We merge the TRACE with NAIC transaction data to expand the sample size. If transactions of the same bond are covered in both datasets, we keep only those reported by TRACE. We follow the data screening procedure in Bessembinder et al. [2009] to eliminate cancelled, corrected, and commission trades.

Monthly data are used in asset pricing and portfolio tests. The LBFI database has breadth of coverage of monthly corporate bond returns, but it ends in March 1998. Datastream provides price information for an extended period but only for the bonds included in the Lehman corporate bond indexes. To expand the bond universe in empirical analysis, we construct monthly returns from TRACE and NAIC databases using the month-end transaction prices, and pool them with the monthly returns obtained from the LBFI and Datastream to create a long-span return series for corporate bonds. Pooling these databases extends the sample period and increases the sample size to facilitate more efficient tests on asset pricing. To avoid double-counting, we keep only one return record if the same bond is covered in more than one dataset. We drop Datastream data whenever returns are available from other sources.[5] When both the Lehman data and transaction data are available, we choose transaction-based return data.

We remove the data where the price or return is problematic. Extreme bond price changes are indicative of recording errors. In addition, we eliminate data for bonds with a maturity of less than one year because liquidity for these issues is low, which subjects them to high pricing errors. To prevent the confounding effects of embedded options, we exclude callable, puttable, convertible, and sinking fund bonds, as well as bonds with a floater or odd frequency of coupon payments. We also drop bonds whose rating we cannot identify. We employ primarily the Moody's rating, but if it is unavailable, we use the Standard and Poor's (S&P) rating when possible. Finally, we match bonds with stocks issued by the same firms. Our sample contains a total of 44,427 bond issues, with about 1.5 million bond-month observations. The sample period is from January 1994 to September 2009.

The monthly corporate bond return as of time $t$ is computed as follows:

$$r_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}} \tag{1}$$

where $P_t$ is the price, $AI_t$ is accrued interest, and $C_t$ is the coupon payment, if any, in month $t$. In constructing monthly returns from TRACE and NAIC data, we first compute daily prices as the trade-size-weighted average of intraday prices over the day following the procedure in Bessembinder et al. [2009] and then use the month-end price to calculate returns. We use the price at the end of each month to calculate the bond's monthly return. If the price record does not fall on the last trading day of the month, we calculate the return by interpolating the last price of the month and the first price of the following month.

Panel A of Exhibit 1 summarizes the data sample by year and rating category. The number of bonds and issuing firms varies over time, and both the number and value of corporate bond issues exhibit an uptrend. The time series also shows a cyclical pattern, with a decline in the number of bond issues and total value in 1999–2000 and 2008–2009. While the proportion of A and BBB firms to the whole sample is fairly stable over the sample period, there is a shift in the distribution of firms in AAA/AA and junk categories. The proportion of firms with a rating below BBB and AAA/AA firms declines over the sample period.

Panel B of Exhibit 1 displays summary statistics of monthly returns of bonds and stocks for firms in the whole sample and in each rating category. We calculate the cross-sectional average of contemporaneous correlations between bonds and stocks at the firm level and autocorrelations in individual bond and stock returns. Individual bonds exhibit a weak positive first-order serial correlation for all rating categories except for AAA/AA bonds. Contemporaneous correlation is positive between stocks and bonds at the firm level. Lower-grade bonds have higher returns and volatility. Consistent with the traditional view, speculative-grade bonds behave more like stocks in that both volatility and concurrent correlation with stock returns are higher for these bonds.

Monthly returns of the long-term government bond index and one-month T-bill are collected from the Federal Reserve Board. The default premium (DEF) is the difference between the monthly returns of long-term investment-grade bonds and government bonds. The long-term investment-grade bond returns are based on the value-weighted market portfolio consisting of all investment-grade bonds in the sample with at least 10 years to maturity, where the weight is determined by the market value of a bond at the beginning of each month. The term premium (TERM) is the difference between the monthly returns of the long-term government bond and the one-month T-bill.

Default and term premium data are used to estimate betas associated with these two risk factors. Besides default and term betas, we estimate betas associated with the Fama–French three factors (Fama and French [1992]). The stock market, SMB (size), and HML (book-to-market) factors are downloaded from Ken French's website.[6]

We construct the monthly series of the Pastor–Stambaugh [2003] and Amihud [2002] liquidity measures using transaction data. For the Pastor–Stambaugh liquidity measure, we first estimate each bond's liquidity (innovations) from time-series regression and then aggregate individual liquidity measures to form the monthly marketwide liquidity series using the method of Pastor and Stambaugh [2003]. A bond's liquidity is estimated in a given month only if there are at least 10 return observations. For the Amihud measure, we calculate the daily average of absolute value of returns divided by dollar volume for each bond and aggregate individual illiquidity measures to give the marketwide illiquidity measure (see Amihud [2002]). We then obtain the innovations from a time-series regression by using a procedure as in Korajczyk and Sadka [2008]. For ease of comparison with the Pastor–Stambaugh liquidity measure, we convert the Amihud illiquidity innovations by adding a negative sign. The converted innovation series is referred to as the Amihud liquidity measure.

Panel C of Exhibit 1 provides summary statistics of factors and correlation among factors used in asset pricing tests. The monthly average stock market return is 0.13%, with a standard deviation of 4.66% over the sample period. Average monthly returns of the *SMB* and *HML* factors are −0.03% and 0.47%. The average monthly term premium is 0.3%, and the default premium is 0.03%. Both the Amihud and Pastor–Stambaugh liquidity measures have means close to zero because they are innovations by construction. Correlations among variables are generally modest over our sample period.

## MOMENTUM SPILLOVER FROM STOCKS TO BONDS

We first examine profitability of the equity momentum spillover strategy using the portfolio approach. This part of the analysis is essentially an exten-

# EXHIBIT 1
## Summary Statistics on Corporate Bonds

This exhibit provides summary statistics of the sample. In any month, each firm included in the sample must have at least one rated straight bond with one or more years to maturity and have a stock traded on the NYSE, AMEX, or NASDAQ. Bond data are obtained from NAIC, TRACE, Datastream, LBFI, and FISD. Equity returns are from the CRSP. Equity returns are matched with returns of bonds issued by the same firm.

Panel A reports the total number of bonds and the number of individual firms as of December 31 of each year. Firms are divided into four rating categories: AAA/AA, A, BBB, and below BBB. For each rating category, the total outstanding face value (in billions) is reported. Panel B provides summary statistics of monthly returns for the whole sample and by rating category. We report the average contemporaneous firm-level correlation between bond and equity returns and average autocorrelations for individual bonds up to lag 4. Panel C reports summary statistics and correlations for the six factors in the asset pricing model: Market, SMB, HML, default, term, and liquidity. Market, SMB, and HML are Fama–French three factors downloaded from Kenneth French's data library. The default factor (DEF) is the difference between the return of a value-weighted portfolio of long-term investment-grade bonds in the sample and the return of long-term government bonds. The term factor (TERM) is the difference between the long-term government bond return and the one-month T-bill rate. Returns are expressed in percentages. PS bond liquidity is the Pastor–Stambaugh corporate bond market liquidity factor, and Amihud bond liquidity is the Amihud corporate bond market liquidity factor normalized to have a unit standard deviation.

**Panel A: Summary of Data by Year**

| | All Firms | | | AAA/AA | | | A | | | BBB | | | Below BBB | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Number of Firms | Number of Bonds | Value | Number of Firms | Number of Bonds | Value | Number of Firms | Number of Bonds | Value | Number of Firms | Number of Bonds | Value | Number of Firms | Number of Bonds | Value |
| 1994 | 952 | 3133 | 555.5 | 108 | 373 | 70.6 | 453 | 1744 | 315.5 | 258 | 776 | 128.6 | 133 | 240 | 42.0 |
| 1995 | 1188 | 4389 | 716.8 | 103 | 676 | 109.3 | 583 | 2416 | 398.3 | 325 | 969 | 149.2 | 177 | 328 | 61.0 |
| 1996 | 1378 | 5226 | 820.0 | 117 | 1002 | 138.2 | 657 | 2661 | 434.3 | 350 | 1103 | 166.7 | 254 | 460 | 85.6 |
| 1997 | 1624 | 6208 | 967.2 | 147 | 1287 | 171.5 | 708 | 2903 | 467.4 | 462 | 1430 | 223.2 | 307 | 588 | 109.0 |
| 1998 | 1908 | 7411 | 1200.2 | 158 | 1604 | 215.3 | 769 | 3131 | 518.0 | 537 | 1746 | 280.5 | 444 | 930 | 186.2 |
| 1999 | 1538 | 5871 | 1073.9 | 132 | 1114 | 228.3 | 608 | 2426 | 395.7 | 381 | 1452 | 256.7 | 417 | 879 | 193.3 |
| 2000 | 1593 | 5779 | 1246.8 | 159 | 1078 | 297.1 | 601 | 2335 | 436.6 | 405 | 1460 | 288.8 | 428 | 906 | 224.2 |
| 2001 | 1980 | 7771 | 1818.0 | 216 | 2035 | 457.5 | 712 | 2610 | 545.5 | 536 | 1834 | 465.8 | 516 | 1292 | 348.8 |
| 2002 | 2186 | 8052 | 2512.0 | 240 | 1779 | 713.4 | 759 | 2669 | 763.8 | 600 | 2028 | 594.4 | 587 | 1576 | 438.0 |
| 2003 | 2662 | 10080 | 3292.6 | 312 | 2378 | 1014.8 | 988 | 3485 | 1008.3 | 687 | 2371 | 702.6 | 675 | 1846 | 565.2 |
| 2004 | 2995 | 14103 | 3888.5 | 361 | 3561 | 1223.9 | 1046 | 5414 | 1105.5 | 829 | 2943 | 862.0 | 759 | 2185 | 689.0 |
| 2005 | 3228 | 17144 | 4117.3 | 365 | 4006 | 1205.4 | 1149 | 7371 | 1160.3 | 864 | 3248 | 934.4 | 850 | 2519 | 810.5 |
| 2006 | 3198 | 18094 | 4611.6 | 378 | 4521 | 1371.5 | 1125 | 7260 | 1345.9 | 865 | 3234 | 966.0 | 830 | 3079 | 917.8 |
| 2007 | 3076 | 18008 | 4436.8 | 350 | 4679 | 1045.7 | 1145 | 7068 | 1373.5 | 804 | 3371 | 1054.1 | 777 | 2890 | 950.9 |
| 2008 | 2058 | 13395 | 3183.1 | 219 | 4132 | 795.2 | 775 | 5107 | 1076.5 | 601 | 2759 | 848.5 | 463 | 1397 | 463.0 |
| 2009 | 1840 | 11180 | 2978.5 | 128 | 1999 | 502.7 | 688 | 4557 | 1176.2 | 602 | 3268 | 869.9 | 422 | 1356 | 429.7 |

**Panel B: Summary Statistics of Bond Returns by Rating Category**

| | | | | Autocorrelation | | | |
|---|---|---|---|---|---|---|---|
| Bond Category | Mean (%) | Standard Deviation (%) | Corr. with Equity | Lag 1 | Lag 2 | Lag 3 | Lag 4 |
| AAA/AA | 0.31 | 1.25 | 0.28 | –0.08 | –0.10 | –0.06 | –0.04 |
| A | 0.46 | 1.49 | 0.32 | 0.01 | –0.06 | –0.09 | –0.05 |
| BBB | 0.48 | 1.73 | 0.33 | 0.03 | –0.06 | –0.07 | –0.05 |
| below BBB | 0.71 | 2.15 | 0.43 | 0.05 | –0.05 | –0.09 | –0.06 |
| All Bonds | 0.49 | 1.69 | 0.36 | 0.03 | –0.07 | –0.08 | –0.05 |
| Equity | 1.05 | 5.21 | | –0.01 | –0.05 | –0.01 | –0.00 |

**Panel C: Summary Statistics of Factors**

| | Summary Statistics of Factors | | | | | Factor Correlations | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bond Category | Mean | Median | Min | Max | Std. | SMB | HML | DEF | TERM | PS Liq. | Amihud Liq. |
| Market | 0.13 | 0.83 | –18.63 | 11.03 | 4.66 | 0.19 | –0.27 | 0.31 | –0.10 | 0.11 | 0.09 |
| SMB | –0.03 | –0.17 | –21.96 | 13.78 | 3.72 | | –0.40 | 0.15 | –0.17 | 0.06 | 0.02 |
| HML | 0.47 | 0.37 | –9.94 | 13.85 | 3.54 | | | –0.06 | 0.14 | –0.03 | 0.07 |
| DEF | 0.03 | –0.02 | –10.75 | 11.51 | 2.09 | | | | –0.72 | 0.08 | 0.30 |
| TERM | 0.30 | 0.49 | –8.98 | 12.86 | 2.72 | | | | | 0.03 | –0.18 |
| PS bond liquidity | 0.00 | 0.03 | –1.33 | 0.36 | 0.18 | | | | | | 0.33 |
| Amihud bond | 0.00 | 0.05 | –4.73 | 2.21 | 1.00 | | | | | | |

sion of the work of Gebhardt et al. [2005] to a larger and more recent data sample that includes also speculative-grade bonds. This analysis serves several purposes. First, using the more recent data, we perform subperiod analyses to see if the momentum spillover effect changes over time. Previous studies have shown that momentum may weaken over time as more traders profit from the momentum strategy. We examine whether this phenomenon also happens to the momentum spillover from stocks to bonds. Second, we document the first evidence on the spillover effect for the speculative-grade bond, which is a vital segment of the corporate bond market. Third, recent availability of high-quality bond transaction data through TRACE allows us to examine the effect of bond trading liquidity on the momentum spillover.

To provide a direct comparison with the Gebhardt et al. study, we employ a similar method in portfolio sorts. At the beginning of each month, all firms are first sorted by their past six-month equity returns into 10 (5) momentum portfolios in univariate (bivariate) sorts. Future bond returns are then calculated for each firm and averaged across firms in each portfolio. The bond return for a firm is the value-weighted return of its bonds, whereby the weight is based on the market value of each bond at the beginning of each month. Future monthly returns are calculated over a holding period $K$. For instance, $K = 1$ represents the average monthly return during the first month after portfolio formation, and $K = 2, 4$ is the average monthly return from months two to four after portfolio formation.

The momentum spillover portfolio in each month consists of all firms that have bond returns for that month. The holding period portfolio return is the average of the current period's returns on the $K$ previous months' portfolios. For instance, $K$ equal to 2 to 4 represents the average of this month's returns for the portfolios formed two, three, and four months ago. This method avoids the overlapping problem in portfolio returns and facilitates calculation of $t$-statistics in the standard way (see Jegadeesh and Titman [1993]).

We first calculate future bond returns for each firm and then average monthly returns across all firms in the portfolio by using both equal and value weights over the holding period. When computing the value-weighted average portfolio return, we use the weight based on the total market value of bonds for each firm at the beginning of each month. Future returns are calculated over different holding horizons. We report the future bond returns both including and excluding the most recent month. The latter accounts for a potential reversal and/or contrarian effect related to microstructure factors (e.g., bid–ask bounce).

## Equity Momentum Spillover

Panel A of Exhibit 2 shows results based on the full sample. The $t$-statistics (in parentheses) are corrected for autocorrelation using the Newey–West [1987] method.[7] Consistent with the finding of Gebhardt et al. [2005], both equal- and value-weighted portfolio returns show a pronounced momentum spillover from stocks to bonds. Firms with high stock returns in the past six months have high future bond returns.

The difference in returns between winner portfolios (portfolio 10) and loser portfolios (portfolio 1) is significantly positive up to seven (four) months after portfolio formation for equal- (value-) weighted returns. A major difference is that our results show higher momentum spillover returns. This could be because our sample contains a large number of bonds with a rating below BBB. As shown later, the momentum spillover return is substantially higher for speculative-grade bonds.

Excluding the extreme portfolios to mitigate the potential data-recording error has little impact on the basic conclusion. The return difference between portfolios 9 and 2 reported at the bottom of Panel A remains quite significant. In addition, the Sharpe ratio shows economic significance of the equity momentum spillover effect. For example, when returns are equally weighted, the Sharpe ratio of the zero-investment bond portfolio for the six-month horizon $K = 2, 7$ is 0.65, which is comparable to that of stocks.

The momentum spillover effect can be stronger for speculative-grade bonds, as they are traded more often at a discount. Lower-grade bonds behave more like stocks (see Kwan [1996]) and may thus have a stronger momentum similar to stocks. Panel B of Exhibit 2 reports results by rating category. Results show a pervasive spillover effect across ratings. The differences in returns between high (portfolio 5) and low (portfolio 1) momentum spillover portfolios are significantly positive for most holding periods.

More importantly, speculative-grade bonds exhibit a much stronger momentum spillover effect.

## Exhibit 2

### Equity Momentum Spillover to Corporate Bonds

This exhibit reports future returns of the stocks and bonds of firms in different stock momentum portfolios. At the beginning of each month from January 1994 to September 2009, all firms in the sample are first divided into portfolios (10 in Panel A, 5 in Panels B, C, and D) based on their past six-month equity returns, and then future returns of their bonds and stocks are reported. The firm's bond return is the value-weighted returns of all traded bonds issued by the firm. We report both equal- and value-weighted portfolio returns in the first two panels. Panel A reports results for the full sample, Panel B by rating category, Panel C by trading variable, and Panel D by rating and trading variable. Future monthly returns are calculated over $K$. For instance, $K = 1$ is the average monthly return during the first month after portfolio formation, and $K = 2, 4$ is average monthly return from months two to four after the portfolio formation. The numbers in parentheses are $t$-statistics adjusted by the Newey–West [1987] method.

**Panel A: Full Sample**

| | Bond Returns | | | | | | | | | | | | Stock Returns | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Equal Weighted | | | | | | Value Weighted | | | | | | EW | VW |
| Portfolio | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=2,7 | K=2,7 |
| 1 | 0.23 | 0.47 | 0.53 | 0.54 | 0.56 | 0.59 | 0.25 | 0.47 | 0.55 | 0.58 | 0.60 | 0.60 | 0.12 | 1.26 |
| 2 | 0.42 | 0.48 | 0.45 | 0.50 | 0.48 | 0.49 | 0.43 | 0.45 | 0.48 | 0.47 | 0.43 | 0.45 | 0.41 | 1.04 |
| 3 | 0.48 | 0.56 | 0.54 | 0.55 | 0.55 | 0.56 | 0.41 | 0.50 | 0.49 | 0.50 | 0.50 | 0.50 | 0.87 | 1.21 |
| 4 | 0.51 | 0.54 | 0.53 | 0.54 | 0.54 | 0.54 | 0.46 | 0.50 | 0.50 | 0.50 | 0.50 | 0.49 | 0.87 | 1.23 |
| 5 | 0.54 | 0.55 | 0.56 | 0.55 | 0.55 | 0.55 | 0.51 | 0.53 | 0.52 | 0.52 | 0.51 | 0.51 | 0.91 | 1.23 |
| 6 | 0.56 | 0.52 | 0.54 | 0.54 | 0.54 | 0.55 | 0.53 | 0.48 | 0.50 | 0.50 | 0.50 | 0.50 | 0.85 | 1.26 |
| 7 | 0.60 | 0.56 | 0.56 | 0.55 | 0.55 | 0.55 | 0.56 | 0.54 | 0.52 | 0.51 | 0.50 | 0.50 | 0.88 | 1.18 |
| 8 | 0.62 | 0.57 | 0.56 | 0.56 | 0.56 | 0.55 | 0.58 | 0.48 | 0.50 | 0.50 | 0.50 | 0.50 | 0.85 | 1.27 |
| 9 | 0.73 | 0.60 | 0.56 | 0.57 | 0.56 | 0.55 | 0.65 | 0.56 | 0.52 | 0.51 | 0.49 | 0.49 | 0.99 | 1.47 |
| 10 | 0.97 | 0.82 | 0.73 | 0.68 | 0.65 | 0.62 | 0.89 | 0.73 | 0.73 | 0.67 | 0.63 | 0.56 | 1.20 | 2.01 |
| 10-1 | 0.74 | 0.35 | 0.20 | 0.14 | 0.08 | 0.03 | 0.64 | 0.27 | 0.18 | 0.09 | 0.03 | –0.04 | 1.08 | 0.75 |
| | (5.82) | (3.41) | (2.18) | (2.02) | (1.35) | (0.59) | (4.98) | (2.57) | (1.80) | (1.13) | (0.17) | (–0.64) | (2.77) | (1.49) |
| Sharpe ratio | 2.27 | 1.07 | 0.70 | 0.62 | 0.44 | 0.18 | 1.53 | 0.66 | 0.47 | 0.28 | 0.10 | –0.16 | 0.63 | 0.39 |
| 9-2 | 0.31 | 0.12 | 0.11 | 0.07 | 0.08 | 0.05 | 0.23 | 0.11 | 0.08 | 0.05 | 0.06 | 0.04 | 0.58 | 0.43 |
| | (5.13) | (2.16) | (3.36) | (2.15) | (2.59) | (1.98) | (3.54) | (1.88) | (1.85) | (1.27) | (1.71) | (1.39) | (2.92) | (1.84) |
| Sharpe ratio | 1.64 | 0.64 | 0.93 | 0.65 | 0.83 | 0.62 | 0.95 | 0.53 | 0.48 | 0.30 | 0.40 | 0.32 | 0.65 | 0.38 |

**Exhibit 2 (Continued)**

**Panel B: By Rating**

| | | Bond Returns | | | | | | | | | | | | Stock Returns | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Equal Weighted | | | | | | Value Weighted | | | | | | EW | VW |
| Rating | Portfolio | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=2,7 | K=2,7 |
| | 1 | 0.38 | 0.43 | 0.47 | 0.48 | 0.48 | 0.48 | 0.36 | 0.42 | 0.42 | 0.43 | 0.46 | 0.46 | 0.87 | 1.18 |
| | 5 | 0.57 | 0.51 | 0.54 | 0.51 | 0.52 | 0.52 | 0.48 | 0.47 | 0.43 | 0.42 | 0.45 | 0.45 | 1.29 | 1.40 |
| AAA/AA | 5-1 | 0.19 | 0.08 | 0.07 | 0.03 | 0.04 | 0.03 | 0.12 | 0.05 | 0.01 | –0.01 | –0.01 | –0.01 | 0.42 | 0.22 |
| | | (3.10) | (1.42) | (1.32) | (0.61) | (1.07) | (0.92) | (2.53) | (1.41) | (0.25) | (–0.18) | (–0.19) | (–0.30) | (0.96) | (0.58) |
| Sharpe ratio | | 0.88 | 0.39 | 0.37 | 0.18 | 0.31 | 0.28 | 0.69 | 0.31 | 0.06 | –0.05 | –0.05 | –0.08 | 0.26 | 0.15 |
| | 1 | 0.37 | 0.51 | 0.52 | 0.51 | 0.56 | 0.60 | 0.36 | 0.35 | 0.42 | 0.42 | 0.46 | 0.48 | 0.57 | 1.16 |
| | 5 | 0.75 | 0.69 | 0.64 | 0.64 | 0.63 | 0.61 | 0.61 | 0.51 | 0.49 | 0.50 | 0.50 | 0.48 | 0.88 | 1.47 |
| A | 5-1 | 0.38 | 0.17 | 0.13 | 0.12 | 0.07 | 0.01 | 0.25 | 0.17 | 0.07 | 0.08 | 0.04 | –0.00 | 0.31 | 0.30 |
| | | (4.40) | (2.16) | (2.01) | (2.28) | (1.51) | (0.26) | (3.70) | (2.18) | (0.99) | (1.17) | (0.69) | (–0.09) | (1.04) | (0.92) |
| Sharpe ratio | | 1.23 | 0.54 | 0.51 | 0.63 | 0.37 | 0.07 | 0.72 | 0.45 | 0.20 | 0.44 | 0.11 | –0.01 | 0.23 | 0.22 |
| | 1 | 0.33 | 0.44 | 0.47 | 0.50 | 0.51 | 0.51 | 0.34 | 0.47 | 0.49 | 0.53 | 0.53 | 0.54 | 0.55 | 1.14 |
| | 5 | 0.70 | 0.63 | 0.63 | 0.61 | 0.60 | 0.59 | 0.74 | 0.62 | 0.61 | 0.58 | 0.56 | 0.56 | 1.12 | 1.94 |
| BBB | 5-1 | 0.36 | 0.18 | 0.16 | 0.11 | 0.10 | 0.08 | 0.39 | 0.15 | 0.12 | 0.05 | 0.03 | 0.02 | 0.57 | 0.79 |
| | | (5.33) | (3.77) | (3.24) | (2.44) | (2.16) | (1.96) | (5.59) | (2.25) | (1.69) | (0.72) | (0.51) | (0.40) | (2.19) | (1.68) |
| Sharpe ratio | | 1.83 | 1.07 | 0.94 | 0.69 | 0.65 | 0.60 | 1.35 | 0.50 | 0.37 | 0.17 | 0.13 | 0.10 | 0.49 | 0.46 |
| | 1 | 0.30 | 0.48 | 0.57 | 0.58 | 0.63 | 0.65 | 0.20 | 0.46 | 0.53 | 0.58 | 0.64 | 0.67 | –0.17 | 1.57 |
| | 5 | 1.13 | 0.96 | 0.86 | 0.76 | 0.71 | 0.68 | 1.12 | 0.98 | 0.88 | 0.73 | 0.66 | 0.62 | 1.45 | 2.36 |
| Below BBB | 5-1 | 0.84 | 0.49 | 0.29 | 0.18 | 0.08 | 0.03 | 0.92 | 0.53 | 0.36 | 0.16 | 0.03 | –0.05 | 1.61 | 0.78 |
| | | (6.23) | (3.74) | (2.63) | (2.11) | (1.08) | (0.41) | (5.21) | (3.11) | (2.51) | (1.44) | (0.26) | (–0.44) | (3.50) | (1.32) |
| Sharpe ratio | | 2.12 | 1.21 | 0.84 | 0.64 | 0.33 | 0.13 | 1.85 | 1.00 | 0.74 | 0.40 | 0.08 | –0.13 | 0.92 | 0.36 |

## EXHIBIT 2 (Continued)

**Panel C: By Trading Variables**

| Univariate Sorts | Portfolio | Bond Returns | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 |
| | | Stock Volume | | | | | | Bond Volume | | | | | | Bond Trading Frequency | | | | | |
| Low | 1 | 0.49 | 0.60 | 0.63 | 0.68 | 0.69 | 0.70 | 0.33 | 0.39 | 0.50 | 0.58 | 0.66 | 0.69 | 0.40 | 0.47 | 0.53 | 0.61 | 0.67 | 0.71 |
| | 5 | 0.84 | 0.77 | 0.72 | 0.67 | 0.67 | 0.67 | 1.18 | 1.02 | 0.85 | 0.81 | 0.77 | 0.73 | 1.28 | 1.04 | 0.90 | 0.83 | 0.77 | 0.73 |
| | 5-1 | 0.35 | 0.17 | 0.09 | −0.00 | −0.02 | −0.03 | 0.85 | 0.63 | 0.35 | 0.23 | 0.11 | 0.04 | 0.88 | 0.58 | 0.37 | 0.21 | 0.09 | 0.03 |
| | | (4.34) | (2.13) | (1.14) | (−0.02) | (−0.35) | (−0.75) | (4.72) | (5.02) | (3.48) | (2.98) | (1.66) | (0.53) | (4.36) | (4.17) | (3.36) | (2.84) | (1.31) | (0.41) |
| High | 1 | 0.23 | 0.35 | 0.41 | 0.47 | 0.50 | 0.52 | 0.38 | 0.46 | 0.49 | 0.51 | 0.54 | 0.56 | 0.36 | 0.47 | 0.48 | 0.52 | 0.55 | 0.57 |
| | 5 | 0.80 | 0.66 | 0.58 | 0.54 | 0.52 | 0.51 | 0.73 | 0.64 | 0.61 | 0.58 | 0.59 | 0.58 | 0.72 | 0.61 | 0.58 | 0.56 | 0.57 | 0.56 |
| | 5-1 | 0.58 | 0.31 | 0.17 | 0.07 | 0.05 | −0.01 | 0.34 | 0.19 | 0.12 | 0.07 | 0.05 | 0.02 | 0.36 | 0.14 | 0.09 | 0.04 | 0.02 | −0.01 |
| | | (4.92) | (2.76) | (1.69) | (0.82) | (0.24) | (−0.25) | (3.82) | (2.42) | (1.59) | (1.00) | (0.75) | (0.25) | (4.03) | (1.68) | (1.17) | (0.50) | (0.25) | (−0.10) |
| H-L | 5-1 | 0.23 | 0.14 | 0.08 | 0.07 | 0.04 | 0.02 | −0.51 | −0.44 | −0.23 | −0.16 | −0.07 | −0.02 | −0.52 | −0.44 | −0.28 | −0.18 | −0.07 | −0.03 |
| | | (3.08) | (1.76) | (1.00) | (0.99) | (0.56) | (0.21) | (−3.34) | (−3.90) | (−2.51) | (−2.19) | (−0.95) | (−0.28) | (−2.96) | (−3.47) | (−2.99) | (−2.38) | (−0.96) | (−0.42) |

| Bivariate Sorts | | Bond Returns | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 |
| Stock Volume | Portfolio | Low Bond Volume | | | | | | High Bond Volume | | | | | |
| Low | 1 | 0.44 | 0.44 | 0.57 | 0.68 | 0.74 | 0.74 | 0.47 | 0.53 | 0.54 | 0.52 | 0.54 | 0.58 |
| | 5 | 1.04 | 1.03 | 0.93 | 0.83 | 0.83 | 0.80 | 0.68 | 0.60 | 0.58 | 0.58 | 0.60 | 0.60 |
| | 5-1 | 0.60 | 0.59 | 0.36 | 0.15 | 0.09 | 0.09 | 0.21 | 0.07 | 0.04 | 0.06 | 0.06 | 0.02 |
| | | (4.17) | (4.37) | (3.39) | (1.65) | (1.01) | (1.38) | (2.36) | (0.86) | (0.59) | (0.92) | (0.89) | (0.38) |
| High | 1 | 0.05 | 0.27 | 0.40 | 0.54 | 0.61 | 0.67 | 0.31 | 0.41 | 0.48 | 0.50 | 0.52 | 0.55 |
| | 5 | 1.16 | 0.94 | 0.75 | 0.74 | 0.72 | 0.70 | 0.79 | 0.66 | 0.62 | 0.58 | 0.57 | 0.55 |
| | 5-1 | 1.11 | 0.68 | 0.35 | 0.20 | 0.11 | 0.03 | 0.48 | 0.25 | 0.14 | 0.08 | 0.08 | 0.00 |
| | | (4.44) | (3.81) | (2.04) | (2.33) | (1.01) | (0.22) | (4.12) | (2.15) | (1.33) | (0.90) | (0.69) | (0.01) |

## EXHIBIT 2 (Continued)

**Panel D: By Rating and Trading Volume**

| Rating | | Portfolio | Bond Returns | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Stock Volume | | | | | | Bond Volume | | | | | |
| | | | *K*=1 | *K*=2 | *K*=2,4 | *K*=2,7 | *K*=2,10 | *K*=2,13 | *K*=1 | *K*=2 | *K*=2,4 | *K*=2,7 | *K*=2,10 | *K*=2,13 |
| | | 1 | 0.53 | 0.56 | 0.57 | 0.54 | 0.56 | 0.56 | 0.47 | 0.42 | 0.48 | 0.54 | 0.51 | 0.48 |
| | Low | 5 | 0.56 | 0.60 | 0.50 | 0.52 | 0.53 | 0.52 | 0.68 | 0.62 | 0.62 | 0.59 | 0.55 | 0.54 |
| | | 5-1 | 0.03 | 0.04 | −0.07 | −0.03 | −0.03 | −0.03 | 0.21 | 0.21 | 0.15 | 0.05 | 0.03 | 0.07 |
| AAA/ AA | | | (0.31) | (0.40) | (−0.87) | (−0.40) | (−0.43) | (−0.60) | (2.14) | (1.48) | (1.42) | (0.68) | (0.53) | (1.08) |
| | | 1 | 0.38 | 0.41 | 0.44 | 0.46 | 0.46 | 0.47 | 0.41 | 0.43 | 0.45 | 0.48 | 0.47 | 0.48 |
| | High | 5 | 0.52 | 0.48 | 0.48 | 0.49 | 0.49 | 0.49 | 0.51 | 0.50 | 0.51 | 0.49 | 0.48 | 0.48 |
| | | 5-1 | 0.14 | 0.08 | 0.04 | 0.03 | 0.03 | 0.02 | 0.10 | 0.07 | 0.06 | 0.01 | 0.01 | 0.00 |
| | | | (2.42) | (1.03) | (0.78) | (0.55) | (0.62) | (0.33) | (1.66) | (0.94) | (0.84) | (0.21) | (0.13) | (0.05) |
| | | 1 | 0.54 | 0.54 | 0.56 | 0.56 | 0.61 | 0.59 | 0.23 | 0.36 | 0.43 | 0.51 | 0.60 | 0.63 |
| | Low | 5 | 0.86 | 0.76 | 0.71 | 0.69 | 0.67 | 0.62 | 0.79 | 0.96 | 0.67 | 0.59 | 0.59 | 0.57 |
| | | 5-1 | 0.32 | 0.21 | 0.15 | 0.13 | 0.06 | 0.03 | 0.57 | 0.60 | 0.24 | 0.08 | −0.01 | −0.06 |
| A | | | (2.86) | (1.65) | (1.37) | (1.28) | (0.61) | (0.42) | (2.40) | (2.52) | (1.65) | (0.71) | (−0.11) | (−0.64) |
| | | 1 | 0.27 | 0.41 | 0.38 | 0.42 | 0.45 | 0.47 | 0.43 | 0.47 | 0.50 | 0.50 | 0.52 | 0.54 |
| | High | 5 | 0.70 | 0.51 | 0.42 | 0.39 | 0.38 | 0.40 | 0.63 | 0.53 | 0.53 | 0.52 | 0.51 | 0.49 |
| | | 5-1 | 0.44 | 0.10 | 0.04 | −0.03 | −0.08 | −0.06 | 0.21 | 0.06 | 0.03 | 0.02 | −0.01 | −0.05 |
| | | | (2.72) | (0.76) | (0.38) | (−0.34) | (−1.12) | (−1.18) | (2.79) | (0.97) | (0.48) | (0.23) | (−0.37) | (−1.20) |
| | | 1 | 0.53 | 0.57 | 0.57 | 0.59 | 0.58 | 0.59 | 0.46 | 0.32 | 0.36 | 0.49 | 0.54 | 0.58 |
| | Low | 5 | 0.65 | 0.55 | 0.57 | 0.59 | 0.61 | 0.60 | 0.79 | 0.58 | 0.57 | 0.65 | 0.65 | 0.62 |
| | | 5-1 | 0.11 | −0.02 | −0.01 | 0.01 | 0.02 | 0.01 | 0.33 | 0.26 | 0.21 | 0.16 | 0.10 | 0.03 |
| BBB | | | (1.60) | (−0.31) | (−0.10) | (0.12) | (0.58) | (0.37) | (1.68) | (2.42) | (2.46) | (2.42) | (1.70) | (0.64) |
| | | 1 | 0.34 | 0.34 | 0.40 | 0.46 | 0.49 | 0.50 | 0.39 | 0.46 | 0.51 | 0.53 | 0.54 | 0.54 |
| | High | 5 | 0.71 | 0.61 | 0.58 | 0.55 | 0.53 | 0.53 | 0.65 | 0.55 | 0.53 | 0.53 | 0.53 | 0.52 |
| | | 5-1 | 0.37 | 0.27 | 0.18 | 0.09 | 0.04 | 0.03 | 0.26 | 0.09 | 0.02 | 0.01 | −0.01 | −0.01 |
| | | | (3.95) | (3.54) | (2.24) | (1.12) | (0.58) | (0.47) | (3.80) | (1.37) | (0.30) | (0.07) | (−0.10) | (−0.23) |
| | | 1 | 0.43 | 0.60 | 0.63 | 0.72 | 0.75 | 0.75 | 0.35 | 0.61 | 0.65 | 0.73 | 0.78 | 0.82 |
| | Low | 5 | 1.06 | 0.94 | 0.84 | 0.81 | 0.80 | 0.79 | 1.47 | 1.09 | 1.02 | 1.00 | 0.94 | 0.87 |
| Below BBB | | 5-1 | 0.63 | 0.34 | 0.21 | 0.08 | 0.05 | 0.04 | 1.13 | 0.49 | 0.36 | 0.27 | 0.16 | 0.05 |
| | | | (4.01) | (2.61) | (2.06) | (1.06) | (0.64) | (0.67) | (4.30) | (1.96) | (2.12) | (2.26) | (1.57) | (0.54) |
| | | 1 | 0.19 | 0.36 | 0.46 | 0.60 | 0.67 | 0.70 | 0.40 | 0.52 | 0.54 | 0.64 | 0.72 | 0.74 |
| | High | 5 | 1.21 | 1.00 | 0.92 | 0.86 | 0.79 | 0.75 | 1.23 | 0.93 | 0.87 | 0.79 | 0.77 | 0.77 |
| | | 5-1 | 1.03 | 0.65 | 0.46 | 0.25 | 0.12 | 0.05 | 0.83 | 0.41 | 0.33 | 0.15 | 0.05 | 0.04 |
| | | | (5.98) | (3.62) | (3.10) | (1.99) | (1.02) | (0.36) | (4.65) | (2.74) | (2.35) | (1.19) | (0.42) | (0.29) |

For example, for the one-month holding period $K = 1$, the return of the zero-investment portfolio is 84 bps ($t = 6.23$) for speculative-grade bonds, but it is only 19 bps ($t = 3.10$) for AAA/AA bonds when returns are equal weighted. The difference is even bigger in proportion for the holding period $K = 2$, in which the return of speculative-grade bonds is about six times that of AAA/AA bonds (0.49 versus 0.08). The Sharpe ratio shows the momentum spillover effect is more economically significant for speculative-grade bonds (e.g., 2.12 versus 0.88 for AAA/AA bonds at $K = 1$). To our knowledge, this is the first evidence on the momentum spillover effect for speculative-grade bonds.

### Liquidity and Equity Momentum Spillover

The momentum spillover effect could stem from low liquidity in the corporate bond market. Corporate bonds are traded less frequently than stocks, and this could induce the momentum spillover effect; information may be impounded into stock and bond prices through trading at different paces. Gebhardt et al. [2005] use trading volume of the firm's equity as a proxy for bond liquidity. While liquidity of corporate bonds is related to liquidity of stocks of the same firm, this relation is less than perfect. Thus, besides stock volume, we use bond trading activity as a direct measure of bond liquidity.

Panel C reports results of momentum spillover portfolios by liquidity proxy. For brevity, we report only equal-weighted portfolio returns, as value-weighted returns give a similar pattern.[8] The first set of results in the upper part of this panel is for portfolio sorts by stock trading volume. Results show that firms with high stock trading volume have a stronger equity momentum spillover effect. The bond return of the zero-investment 5-1 portfolio at $K = 1$ for firms with high stock volume is 58 bps, which is significantly greater than that (35 bps) for firms with low stock volume at the 1% level ($t = 3.08$). A possible explanation for this difference is that firms with higher stock volume have higher asymmetric information, which is spilled over from stocks to bonds that are less frequently traded, thereby inducing a stronger momentum spillover effect.

We next report results of portfolio sorts by bond volume. The information spillover effect is expected to be stronger for firms with low bond trading volume since information impounded in stock prices may have not been fully reflected in bond prices in the short term due to thin volume. Results support this hypothesis. Firms with the lowest bond volume have the strongest equity momentum spillover effect. The bond return of the zero-investment 5-1 portfolio is 85 bps per month with a $t$ value of 4.72 for firms with low bond trading volume at $K = 1$, as opposed to a return of 34 bps with a $t$ value of 3.82 for firms with high bond trading volume. The high–low return difference is −51 bps per month, with a $t$ value of −3.34. This return spread in absolute terms is much larger than that (0.23) stratified by stock trading volume. Results for $K = 2$ and other holding periods are similar. Thus, portfolio sorts by bond volume appear to be more effective in assessing the liquidity effect.

Results by bond trading frequency show a similar pattern. Firms with low bond trading frequency experience a high equity momentum spillover effect. The difference in momentum spillover returns between high and low trading frequency groups at $K = 1$ is −52 bps per month ($t = -2.96$), which is comparable to the spread of portfolios sorted by bond volume. Thus, results are robust to the choice of different bond trading liquidity measures.

Finally, we examine the joint effect of stock and bond trading activities. For brevity, we report only the results sorted by bond and stock volumes because those based on trading frequency are similar. Firms with low bond volume or high stock volume have a stronger spillover effect, and combining these effects could polarize the results. As shown in the lower part of Panel C, this is indeed the case. The zero-investment 5-1 portfolio return of 111 bps at $K = 1$ for firms with high stock volume and low bond volume is about five times that (21 bps) for firms with low stock volume and high bond volume.

### Interactive Effect of Liquidity and Credit Quality

Bonds with low ratings have high momentum spillover. This effect can interact with trading liquidity in the momentum spillover. To explore this possibility, we divide the sample by rating and trading liquidity. For brevity, we report results based on volume only. Results in Panel D show that firms with a high rating and low stock volume have a weaker momentum spillover effect.

For example, for firms with an AAA/AA rating and low stock volume, the monthly return of the zero-investment 5-1 portfolio is only 3 bps at $K = 1$, which is not significant statistically. In stark contrast, for firms with a rating below BBB and high stock volume, the monthly return of the zero-investment 5-1 portfolio is 103 bps with a $t$ value of 5.98. The zero-investment 5-1 portfolio returns are significant at the 5% level for all holding periods up to seven months for firms with high stock volume and a rating below BBB, whereas they are all insignificant for AAA/AA firms with low stock volume. Results show a significant interactive effect of stock trading and credit quality.

Results by rating and bond volume show even larger return spreads. For firms with a rating below BBB and low bond volume, the return of the zero-investment 5-1 portfolio at $K = 1$ is 113 bps per month with a $t$ value of 4.30, compared with a return spread of 10 bps with a $t$ value of 1.66 for AAA/AA firms with high bond volume.

Summarizing, liquidity and credit quality both affect the momentum spillover from stocks to bonds. High stock trading volume accompanied by low bond trading activity results in a greater momentum spillover effect. The liquidity effect varies by bond quality. The momentum spillover effect is much stronger for low-grade firms with high stock volume and low bond volume.

### Equity Momentum Spillover in Subperiods

The significant equity momentum spillover effect suggests that a strategy based on past stock returns is profitable for bond trading. If more traders use this information to capitalize on the profitable opportunity, the momentum spillover effect should weaken over time. We examine this possibility by dividing the sample period into two subperiods: 1994–2001 and 2002–2009. The second subperiod covers the period after the 2002 TRACE reform. During this period, more information was disclosed in the corporate bond market, which could reduce the constraint of arbitrage and make it easier for traders to exploit the profitable opportunity.

Panel A of Exhibit 3 shows that the momentum spillover effect generally declines in the second subperiod. When returns are equally weighted, bond returns of the zero-investment 10-1 portfolios are 47, 35, 24, and 16 bps per month for $K = 2$, (2,4), (2,7) and (2,10) in the first subperiod, all significant at least at the 5% level. Correspondingly, they are only 23, 5, 4, and 0 bps in the second subperiod, none of which is significant at the 5% level. The decrease in momentum profits is larger for value-weighted returns.

Panel B reports results for subsamples stratified by rating. The trend of equity momentum spillover varies by rating category. For investment-grade bonds, the momentum spillover effect decreases more for BBB and A bonds for $K > 1$, whereas the change is smaller for AAA/AA bonds. The largest decline in the momentum spillover effect occurs for speculative-grade bonds. For example, returns of the zero-investment 5-1 portfolios are 65, 46, 28, 13, and 5 bps per month for $K = 2$, (2,4), (2,7), (2,10) and (2,13) in the first subperiod but only 32, 11, 7, 3, and 0 bps in the second subperiod when portfolio returns are equal weighted.

Results for value-weighted portfolio returns are similar. The reason for the larger change for speculative-grade bonds is not immediately clear. It could stem from the improvement on transparency (information efficiency) and liquidity after the 2002 TRACE reform for these bonds, which made it easier for traders to exploit profitable opportunities. In addition, the flight-to-quality during the subprime crisis could have weakened the momentum spillover effect for low-quality bonds because investors shunned high-risk bonds.

## PRICING LIQUIDITY RISK WITH MOMENTUM SPILLOVER PORTFOLIOS

The results in the preceding section show a significant momentum spillover from stocks to corporate bonds issued by the same firm. Bonds of firms whose stocks have performed well in the past six months outperform bonds of firms whose stocks have performed poorly in the past. This momentum spillover effect is more pronounced for lower-quality and less liquid bonds. In this section, we investigate whether liquidity risk is important for explaining the momentum spillover anomaly.

### Risk-Adjusted Returns of Momentum Spillover Portfolios

To explore the role of liquidity risk, we form two sets of portfolios from the sample to give greater cross-sectional dispersion in expected portfolio returns. The first set contains 25 momentum spillover portfo-

# Exhibit 3

## Momentum Spillover: Subperiod Analysis

This exhibit reports future returns for stocks and bonds of firms in different stock momentum portfolios for two subperiods: 1994–2001 and 2002–2009. At the beginning of each month, all firms in the sample are divided into portfolios (10 in Panel A, 5 in Panel B) based on their past six-month equity returns. Both equal- and value-weighted average future portfolio returns are reported.

Panel A reports results of the full sample and Panel B reports results by rating category. Future monthly returns are calculated over holding period $K$. For example, $K = 1$ represents the average monthly return during the first month after portfolio formation and $K = 2,4$ represents average monthly return from months two to four after portfolio formation. The numbers in parentheses are $t$-statistics adjusted by the Newey–West [1987] method.

| | | Bond Returns | | | | | | | | | | | | Stock Returns | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Equal Weighted | | | | | | Value Weighted | | | | | | EW | VW |
| Portfolio | | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | K=2,7 | K=2,7 |
| **Panel A: Full Sample** | | | | | | | | | | | | | | | |
| Subperiod 1: 1994–2001 | | | | | | | | | | | | | | | |
| | 1 | 0.11 | 0.31 | 0.36 | 0.42 | 0.47 | 0.50 | 0.10 | 0.34 | 0.39 | 0.46 | 0.51 | 0.54 | 0.28 | 1.53 |
| | 5 | 0.57 | 0.53 | 0.55 | 0.54 | 0.54 | 0.54 | 0.53 | 0.49 | 0.51 | 0.51 | 0.50 | 0.50 | 1.09 | 1.73 |
| | 10 | 0.88 | 0.78 | 0.71 | 0.66 | 0.62 | 0.59 | 0.75 | 0.67 | 0.61 | 0.58 | 0.55 | 0.52 | 1.70 | 2.60 |
| | 10-1 | 0.77 | 0.47 | 0.35 | 0.24 | 0.16 | 0.09 | 0.65 | 0.33 | 0.22 | 0.12 | 0.04 | −0.01 | 1.42 | 1.07 |
| | | (3.94) | (3.33) | (3.11) | (2.72) | (2.18) | (1.25) | (3.23) | (2.53) | (1.94) | (1.31) | (0.50) | (−0.15) | (2.87) | (1.51) |
| | 9-2 | 0.21 | 0.13 | 0.08 | 0.08 | 0.08 | 0.05 | 0.15 | 0.12 | 0.04 | 0.04 | 0.03 | 0.02 | 0.73 | 0.49 |
| | | (2.99) | (2.82) | (1.98) | (2.28) | (2.38) | (1.82) | (1.56) | (1.94) | (0.89) | (0.98) | (0.99) | (0.70) | (2.86) | (1.81) |
| Subperiod 2: 2002–2009 | | | | | | | | | | | | | | | |
| | 1 | 0.35 | 0.63 | 0.70 | 0.66 | 0.66 | 0.68 | 0.41 | 0.60 | 0.71 | 0.70 | 0.71 | 0.67 | −0.06 | 0.98 |
| | 5 | 0.50 | 0.56 | 0.57 | 0.57 | 0.56 | 0.56 | 0.48 | 0.57 | 0.54 | 0.53 | 0.52 | 0.51 | 0.73 | 0.71 |
| | 10 | 1.06 | 0.86 | 0.76 | 0.70 | 0.67 | 0.65 | 1.03 | 0.80 | 0.84 | 0.75 | 0.72 | 0.59 | 0.67 | 1.40 |
| | 10-1 | 0.70 | 0.23 | 0.05 | 0.04 | 0.00 | −0.03 | 0.62 | 0.20 | 0.13 | 0.06 | 0.01 | −0.08 | 0.73 | 0.42 |
| | | (4.48) | (1.61) | (0.38) | (0.40) | (0.05) | (−0.31) | (4.10) | (1.28) | (0.81) | (0.44) | (0.09) | (−0.69) | (1.21) | (0.59) |
| | 9-2 | 0.41 | 0.11 | 0.13 | 0.06 | 0.07 | 0.05 | 0.31 | 0.10 | 0.12 | 0.07 | 0.08 | 0.07 | 0.42 | 0.37 |
| | | (4.36) | (1.06) | (2.78) | (1.08) | (1.48) | (1.17) | (3.78) | (0.98) | (1.65) | (0.90) | (1.42) | (1.21) | (1.39) | (0.96) |
| **Panel B: By Rating** | | | | | | | | | | | | | | | |
| AAA/AA | | | | | | | | | | | | | | | |
| 1994– | 1 | 0.46 | 0.49 | 0.54 | 0.50 | 0.50 | 0.50 | 0.43 | 0.46 | 0.48 | 0.47 | 0.46 | 0.46 | 0.99 | 1.77 |
| 2001 | 5 | 0.60 | 0.55 | 0.58 | 0.54 | 0.55 | 0.55 | 0.51 | 0.49 | 0.48 | 0.46 | 0.47 | 0.47 | 1.46 | 1.93 |
| | 5-1 | 0.14 | 0.05 | 0.04 | 0.03 | 0.05 | 0.05 | 0.08 | 0.03 | 0.00 | −0.01 | 0.01 | 0.01 | 0.47 | 0.16 |
| | | (1.99) | (0.75) | (0.69) | (0.75) | (1.33) | (1.42) | (1.96) | (0.78) | (0.12) | (−0.53) | (0.30) | (0.60) | (1.57) | (0.47) |
| 2002– | 1 | 0.29 | 0.37 | 0.41 | 0.45 | 0.46 | 0.46 | 0.29 | 0.38 | 0.36 | 0.39 | 0.45 | 0.45 | 0.75 | 0.57 |
| 2009 | 5 | 0.53 | 0.48 | 0.50 | 0.47 | 0.49 | 0.48 | 0.45 | 0.45 | 0.39 | 0.39 | 0.43 | 0.42 | 1.13 | 0.86 |
| | 5-1 | 0.24 | 0.11 | 0.09 | 0.02 | 0.03 | 0.02 | 0.16 | 0.07 | 0.02 | −0.00 | −0.02 | −0.03 | 0.38 | 0.29 |
| | | (2.46) | (1.22) | (1.14) | (0.25) | (0.48) | (0.25) | (1.85) | (1.18) | (0.30) | (−0.05) | (−0.33) | (−0.58) | (0.45) | (0.42) |
| A | | | | | | | | | | | | | | | |
| 1994– | 1 | 0.33 | 0.39 | 0.41 | 0.39 | 0.47 | 0.49 | 0.37 | 0.36 | 0.40 | 0.44 | 0.48 | 0.50 | 0.80 | 1.51 |
| 2001 | 5 | 0.69 | 0.62 | 0.57 | 0.56 | 0.56 | 0.55 | 0.59 | 0.52 | 0.49 | 0.52 | 0.54 | 0.51 | 1.29 | 1.98 |
| | 5-1 | 0.37 | 0.23 | 0.16 | 0.17 | 0.09 | 0.05 | 0.23 | 0.16 | 0.09 | 0.08 | 0.05 | 0.01 | 0.49 | 0.47 |
| | | (3.98) | (3.56) | (2.73) | (2.44) | (1.89) | (1.05) | (2.31) | (1.87) | (1.30) | (1.20) | (0.99) | (0.19) | (1.42) | (1.39) |
| 2002– | 1 | 0.42 | 0.64 | 0.63 | 0.63 | 0.65 | 0.72 | 0.35 | 0.34 | 0.44 | 0.41 | 0.43 | 0.47 | 0.34 | 0.79 |
| 2009 | 5 | 0.82 | 0.76 | 0.72 | 0.72 | 0.69 | 0.69 | 0.63 | 0.51 | 0.49 | 0.48 | 0.46 | 0.45 | 0.47 | 0.93 |
| | 5-1 | 0.40 | 0.11 | 0.10 | 0.09 | 0.04 | −0.03 | 0.28 | 0.18 | 0.05 | 0.07 | 0.03 | −0.02 | 0.13 | 0.14 |
| | | (2.69) | (0.77) | (0.85) | (0.99) | (0.54) | (−0.44) | (2.93) | (1.38) | (0.39) | (0.65) | (0.25) | (−0.19) | (0.26) | (0.24) |

**Exhibit 3 (Continued)**

| Portfolio | | Bond Returns: Equal Weighted K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | Bond Returns: Value Weighted K=1 | K=2 | K=2,4 | K=2,7 | K=2,10 | K=2,13 | Stock Returns: EW K=2,7 | Stock Returns: VW K=2,7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BBB | | | | | | | | | | | | | | | |
| 1994– | 1 | 0.27 | 0.39 | 0.40 | 0.43 | 0.43 | 0.44 | 0.29 | 0.40 | 0.41 | 0.43 | 0.43 | 0.45 | 0.75 | 1.31 |
| 2001 | 5 | 0.64 | 0.59 | 0.59 | 0.58 | 0.57 | 0.56 | 0.62 | 0.55 | 0.55 | 0.55 | 0.54 | 0.53 | 1.46 | 2.42 |
| | 5-1 | 0.36 | 0.20 | 0.19 | 0.15 | 0.14 | 0.12 | 0.33 | 0.15 | 0.14 | 0.12 | 0.11 | 0.07 | 0.70 | 1.21 |
| | | (3.15) | (3.66) | (2.54) | (2.43) | (2.33) | (2.20) | (3.49) | (2.45) | (2.44) | (2.26) | (2.19) | (1.40) | (1.87) | (1.61) |
| 2002– | 1 | 0.40 | 0.50 | 0.54 | 0.57 | 0.58 | 0.58 | 0.40 | 0.55 | 0.58 | 0.63 | 0.63 | 0.62 | 0.34 | 0.97 |
| 2009 | 5 | 0.76 | 0.67 | 0.66 | 0.65 | 0.63 | 0.63 | 0.86 | 0.69 | 0.66 | 0.60 | 0.58 | 0.59 | 0.78 | 1.29 |
| | 5-1 | 0.37 | 0.16 | 0.12 | 0.07 | 0.05 | 0.05 | 0.46 | 0.14 | 0.08 | −0.02 | −0.05 | −0.03 | 0.43 | 0.36 |
| | | (5.02) | (2.03) | (2.04) | (1.09) | (0.82) | (0.72) | (4.47) | (1.25) | (0.68) | (−0.18) | (−0.47) | (−0.35) | (1.21) | (0.67) |
| Below BBB | | | | | | | | | | | | | | | |
| 1994– | 1 | 0.23 | 0.31 | 0.40 | 0.52 | 0.60 | 0.64 | 0.10 | 0.28 | 0.39 | 0.51 | 0.62 | 0.67 | −0.16 | 1.84 |
| 2001 | 5 | 1.07 | 0.96 | 0.87 | 0.80 | 0.73 | 0.69 | 1.05 | 0.93 | 0.85 | 0.75 | 0.66 | 0.60 | 2.09 | 3.12 |
| | 5-1 | 0.84 | 0.65 | 0.46 | 0.28 | 0.13 | 0.05 | 0.95 | 0.65 | 0.46 | 0.24 | 0.03 | −0.07 | 2.24 | 1.29 |
| | | (4.56) | (3.20) | (2.95) | (2.80) | (1.60) | (0.65) | (4.05) | (2.72) | (2.18) | (1.52) | (0.24) | (−0.49) | (4.07) | (1.52) |
| 2002– | 1 | 0.36 | 0.65 | 0.73 | 0.65 | 0.65 | 0.66 | 0.31 | 0.64 | 0.67 | 0.64 | 0.65 | 0.66 | −0.18 | 1.29 |
| 2009 | 5 | 1.19 | 0.97 | 0.84 | 0.71 | 0.68 | 0.66 | 1.20 | 1.04 | 0.92 | 0.72 | 0.67 | 0.64 | 0.78 | 1.55 |
| | 5-1 | 0.83 | 0.32 | 0.11 | 0.07 | 0.03 | 0.00 | 0.88 | 0.40 | 0.25 | 0.08 | 0.02 | −0.02 | 0.96 | 0.26 |
| | | (4.28) | (2.10) | (0.80) | (0.52) | (0.24) | (0.03) | (3.45) | (1.70) | (1.35) | (0.51) | (0.13) | (−0.12) | (1.32) | (0.33) |

lios constructed from the entire sample. These portfolios contain excess returns of bond portfolios formed by past (6-month) stock returns. The second set contains 5 momentum spillover portfolios for each rating group, with a total of 20 portfolios. This set of portfolios allows us to examine whether liquidity risk pricing in momentum spillover portfolio returns is an intra- or interrating effect. Portfolio returns are all equally weighted.

Fama and French [1993] study common factors of corporate bonds and find that term and default premiums capture most variations in corporate bond returns. Using more recent data, Elton et al. [2001] find that the Fama–French three factors can explain variations in corporate bond returns. Based on these findings, we estimate the following two models:

$$r_{pt} - r_{ft} = \alpha + \beta_1 DEF_t + \beta_2 TERM_t + \varepsilon_t \quad (2)$$

$$r_{pt} - r_{ft} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 DEF_t + \beta_5 TERM_t + \varepsilon_t \quad (3)$$

where $MKT_t$ is the stock market excess return, $SMB_t$ (small minus big) is the size factor, $HML_t$ (high minus low) is the book-to-market factor, $DEF_t$ is the default premium, and $TERM_t$ is the term premium.

Exhibit 4 reports estimates of risk-adjusted returns ($\alpha$) from the two- and five-factor models as well as excess returns of momentum spillover portfolios. Parameters of Models (2) and (3) are estimated from the time-series regression of bond portfolio returns using the full sample. Panel A shows results for the 25 momentum spillover portfolios. On average, past stock winners (P25) earn 90 bps in bond returns per month, whereas past stock losers (P1) lose 4 bps per month in bond returns. The monthly bond return spread is 94 bps, with a $t$ value of 8.55. Excluding the extreme portfolios gives a monthly bond return of 55 bps for the zero-investment 24-2 portfolio, with a $t$ value of 6.17.

Risk-adjusted returns ($\alpha$) show a similar pattern, with past stock winners earning abnormal future bond returns. The risk-adjusted return for the zero-investment 25-1 portfolio is 89 bps with a $t$ value of 7.31 for the two-factor model and 88 bps with a $t$ value of 7.17 for the five-factor model. When excluding extreme portfolios, risk-adjusted returns for the zero-investment 24-2 portfolio are 45 and 44 bps, with $t$ values of 4.67 and 4.61 for the two- and five-factor models, respectively.

## EXHIBIT 4

### Risk-Adjusted Returns of Equity Momentum Spillover Portfolios

This exhibit reports risk-adjusted returns (α) of momentum spillover portfolios relative to the two-factor (DEF and TERM) model and the five-factor model (the Fama–French three factors, DEF, and TERM). Panel A reports results for 25 equity momentum spillover portfolios formed from the full sample. Panel B reports results by rating category, whereby firms are grouped into four rating categories, AAA/AA, A, BBB, and below BBB, and five equity momentum spillover portfolios are formed for each rating category. Risk-adjusted (α) is estimated from the time-series regression of portfolio returns at $K = 1$ using the full sample.

| | | | Two-Factor Model | | Five-Factor Model | |
|---|---|---|---|---|---|---|
| **Ranking** | **Excess Return** | ***t*** | **α** | ***t*** | **α** | ***t*** |
| **Panel A: Momentum Portfolios** | | | | | | |
| 1 | −0.04 | −0.28 | −0.13 | −1.35 | −0.18 | −2.12 |
| 2 | −0.02 | −0.13 | −0.10 | −0.97 | −0.16 | −1.74 |
| 3 | 0.04 | 0.34 | −0.10 | −1.20 | −0.14 | −1.95 |
| 4 | 0.13 | 1.15 | 0.00 | −0.06 | −0.04 | −0.55 |
| 5 | 0.19 | 1.87 | 0.08 | 1.08 | 0.04 | 0.59 |
| 6 | 0.16 | 1.57 | 0.00 | 0.03 | −0.05 | −0.67 |
| 7 | 0.19 | 1.91 | 0.04 | 0.45 | −0.01 | −0.19 |
| 8 | 0.18 | 1.68 | 0.01 | 0.16 | −0.05 | −0.64 |
| 9 | 0.21 | 2.28 | 0.07 | 0.93 | 0.02 | 0.26 |
| 10 | 0.26 | 2.62 | 0.10 | 1.30 | 0.06 | 0.86 |
| 11 | 0.26 | 2.55 | 0.09 | 1.23 | 0.06 | 0.80 |
| 12 | 0.24 | 2.35 | 0.07 | 0.97 | 0.03 | 0.46 |
| 13 | 0.24 | 2.41 | 0.08 | 1.00 | 0.02 | 0.31 |
| 14 | 0.24 | 2.44 | 0.07 | 1.00 | 0.03 | 0.45 |
| 15 | 0.29 | 3.10 | 0.14 | 1.94 | 0.10 | 1.48 |
| 16 | 0.29 | 3.15 | 0.14 | 2.03 | 0.11 | 1.66 |
| 17 | 0.31 | 3.19 | 0.15 | 2.09 | 0.11 | 1.57 |
| 18 | 0.32 | 3.09 | 0.16 | 1.96 | 0.12 | 1.53 |
| 19 | 0.30 | 3.14 | 0.14 | 1.95 | 0.09 | 1.43 |
| 20 | 0.35 | 3.38 | 0.18 | 2.32 | 0.14 | 1.88 |
| 21 | 0.40 | 4.39 | 0.25 | 3.61 | 0.21 | 3.21 |
| 22 | 0.42 | 3.89 | 0.26 | 3.07 | 0.20 | 2.58 |
| 23 | 0.44 | 3.91 | 0.28 | 3.11 | 0.23 | 2.76 |
| 24 | 0.53 | 4.36 | 0.35 | 3.45 | 0.28 | 3.02 |
| 25 | 0.90 | 6.57 | 0.76 | 6.56 | 0.70 | 6.54 |
| 25-1 | 0.94 | 8.55 | 0.89 | 7.31 | 0.88 | 7.17 |
| 24-2 | 0.55 | 6.17 | 0.45 | 4.67 | 0.44 | 4.61 |
| **Panel B: By Rating** | | | | | | |
| AAA/AA | | | | | | |
| 1 | 0.08 | 0.93 | −0.04 | −0.63 | −0.04 | −0.65 |
| 5 | 0.27 | 3.15 | 0.12 | 2.29 | 0.12 | 2.23 |
| 5-1 | 0.19 | 3.10 | 0.16 | 2.27 | 0.16 | 2.28 |
| A | | | | | | |
| 1 | 0.07 | 0.70 | −0.07 | −0.91 | −0.11 | −1.54 |
| 5 | 0.46 | 3.78 | 0.27 | 2.79 | 0.21 | 2.45 |
| 5-1 | 0.38 | 4.40 | 0.34 | 4.35 | 0.32 | 4.15 |
| BBB | | | | | | |
| 1 | 0.04 | 0.34 | −0.12 | −1.66 | −0.14 | −2.11 |
| 5 | 0.40 | 3.92 | 0.22 | 3.03 | 0.19 | 2.64 |
| 5-1 | 0.36 | 5.33 | 0.34 | 5.67 | 0.33 | 5.54 |
| Below BBB | | | | | | |
| 1 | 0.01 | 0.01 | 0.01 | 0.13 | −0.06 | −0.65 |
| 5 | 0.84 | 6.41 | 0.71 | 6.44 | 0.65 | 6.21 |
| 5-1 | 0.83 | 6.23 | 0.70 | 6.09 | 0.72 | 6.58 |

Panel B reports excess returns and risk-adjusted returns by rating category. Risk-adjusted returns (α) for each of the 20 portfolios are estimated from time-series regressions of the factor models in (2) and (3) using the data for the whole sample period. Within each rating category, past stock winners (P5) earn higher bond returns than past stock losers (P1). Monthly return spreads between winner and loser portfolios increase as the rating decreases. The monthly return spread (5–1) is 19 bps with a $t$ value of 3.10 for AAA/AA firms and 83 bps with a $t$ value of 6.23 for firms with a rating below BBB. Results for risk-adjusted return (α) spreads are similar. Within each rating group, winner portfolios have high risk-adjusted returns. Risk-adjusted returns increase with credit risk. For the five-factor model, risk-adjusted returns of the zero-investment 5-1 portfolios range from 16 to 72 bps with $t$ values of 2.28 and 6.58, respectively. Results show that the equity momentum spillover exhibits an interrating effect.

### Estimates of Liquidity Factor Loadings

We estimate betas for each momentum portfolio by using a six-factor model that includes the Fama–French three factors, default and term premiums, and a liquidity factor to explore the role of liquidity risk in the equity momentum spillover. Specifically, the liquidity beta is estimated along with other betas from a time-series regression of the following model:

$$r_{pt} - r_{ft} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 DEF_t + \beta_5 TERM_t + \beta_6 L_t + \varepsilon_t \quad (4)$$

where $L_t$ is the added liquidity factor, which can be either the Amihud or Pastor–Stambaugh measure. Betas are estimated from the time-series regression using the full sample.

Panel A of Exhibit 5 shows estimates of liquidity betas for the 25 momentum spillover portfolios. Bond portfolios formed by past equity returns load positively on both the Amihud and Pastor–Stambaugh liquidity factors, and most liquidity betas are significant at least at the 5% level. High momentum spillover portfolios have large liquidity betas. The return of the zero-investment 25-1 portfolio has a liquidity loading of 1.41 (0.26) with a *t* value of 2.08 (2.12) when using the Pastor–Stambaugh (Amihud) measure as the liquidity factor. The liquidity loading for returns of the zero-investment 24-2 portfolio is naturally smaller but remains significant.

Panel B reports estimates of liquidity factor loadings in the six-factor model for the 20 portfolios formed by past equity returns in different rating categories. Within each rating category, high momentum spillover portfolios have large liquidity betas. The return of the zero-investment 5-1 portfolio for speculative-grade bonds has a liquidity loading of 0.38 (1.72) with a *t* value of 3.55 (2.91) when using the Amihud (Pastor–Stambaugh) measure as the liquidity factor. By contrast, liquidity loadings associated with returns of the zero-investment 5-1 portfolios for AAA/AA bonds are only 0.05 (0.25) with a *t* value of 0.70 (0.66) when using the Amihud (Pastor–Stambaugh) liquidity measure. Clearly, returns of the momentum spillover strategy are more sensitive to liquidity shocks for firms with a rating below BBB.

Exhibits 6 and 7 plot the relationship between mean portfolio excess returns and liquidity betas for the 25 momentum spillover portfolios and the 20 spillover portfolios (by rating), respectively. In Exhibit 6, excess returns of bond portfolios formed by firms' past equity returns increase with both the Amihud and Pastor–Stambaugh liquidity betas. In Exhibit 7, excess returns of portfolios are positively related to the liquidity beta across rating categories. High momentum spillover portfolios of lower-grade firms have higher loadings on the liquidity factor. The positive relation between liquidity loadings and credit risk suggests that liquidity risk pricing is partly an interrating effect. The graphs illustrate that bond excess returns increase with liquidity loadings of bond portfolios formed by past equity returns. The statistical significance of the positive relation between excess returns of momentum spillover portfolios and liquidity loadings is tested by the cross-sectional regression below.

## Cross-Sectional Regression Tests

Momentum spillover portfolio returns are sensitive to liquidity risk, and liquidity beta is positively related to excess returns of portfolios. To test the significance of this positive relation and to estimate the magnitude of the liquidity risk premium, we conduct cross-sectional regressions. We estimate betas from the time-series regression using the full sample and perform cross-sectional tests in each month. The cross-sectional test model is

$$E[R_i] = \gamma_0 + \gamma'\beta_i \tag{5}$$

where $E[R_i]$ denotes the expected excess return of portfolio *i*, $\beta_i$ contains factor loadings estimated from time-series regressions of (2)–(4), and $\gamma$ is a vector of risk prices. Betas are first estimated from the full sample, and then the cross-sectional test is performed each month based on these beta estimates. Mean and standard errors of $\gamma_0$ and $\gamma$ are calculated from the time series of parameter estimates from the cross-sectional regression each month. Because the cross-sectional test is based on beta estimates rather than true values, it is subject to the error-in-variable (EIV) problem. We use the method suggested by Shanken [1992] to correct this bias in standard error estimates.

The coefficients from the ordinary least squares (OLS) cross-sectional regression are averaged over time using the Fama–MacBeth [1973] methodology. Litzenberger and Ramaswamy [1979] show that this OLS procedure is inefficient when volatility is time varying. Thus, we also use the weighted least squares (WLS) methodology to correct inefficiency. However, unlike their method, we adopt the Shanken–Zhou [2007] method, which uses the covariance–variance matrix of portfolio return residuals from the first-step time-series regression as weights in the cross-sectional regression, and correct the EIV problem by the Shanken [1992] method. Adjusted $R^2$ of WLS regressions are calculated using the method of Kandel and Stambaugh [1995]. We report both OLS and WLS results in the cross-sectional asset pricing test.

### Cross-Sectional Regression Results for 25 Momentum Spillover Portfolios

Panel A of Exhibit 8 reports results of the cross-sectional asset pricing test based on returns of 25 momentum

## Exhibit 5

### Liquidity Factor Loadings of Equity Momentum Spillover Portfolios

This exhibit reports the loadings of equity momentum spillover portfolios on the Amihud and Pastor–Stambaugh liquidity factors and the corresponding *t*-statistics. The loadings are estimated from a time-series regression of excess portfolio returns of bonds on the Fama–French three factors, DEF, TERM, and a liquidity factor, which can be either the Amihud or the Pastor–Stambaugh measure. Panel A reports results for 25 equity momentum spillover portfolios formed from the full sample. Panel B reports results by rating category, whereby firms are grouped into four rating categories, AAA/AA, A, BBB, and below BBB, and for each rating group five equity momentum spillover portfolios are formed. Liquidity loading ($\beta$) is estimated from the time-series regression of portfolio returns at K = 1 using the full sample.

| | Amihud Liquidity Factor | | Pastor–Stambaugh Liquidity Factor | |
|---|---|---|---|---|
| **Ranking** | **Liquidity Loading** | ***t*** | **Liquidity Loading** | ***t*** |
| **Panel A: Momentum Portfolios** | | | | |
| 1 | 0.21 | 2.08 | 0.40 | 0.80 |
| 2 | 0.22 | 2.37 | 0.61 | 1.21 |
| 3 | 0.32 | 3.73 | 0.54 | 1.30 |
| 4 | 0.23 | 2.96 | 0.73 | 2.03 |
| 5 | 0.27 | 3.67 | 0.75 | 2.03 |
| 6 | 0.37 | 5.39 | 1.50 | 3.70 |
| 7 | 0.37 | 5.41 | 1.04 | 2.28 |
| 8 | 0.33 | 4.75 | 1.60 | 4.26 |
| 9 | 0.33 | 5.08 | 0.82 | 2.24 |
| 10 | 0.26 | 3.71 | 1.35 | 3.51 |
| 11 | 0.34 | 4.76 | 0.86 | 1.83 |
| 12 | 0.26 | 3.90 | 1.24 | 3.35 |
| 13 | 0.34 | 5.08 | 1.63 | 4.43 |
| 14 | 0.30 | 4.46 | 1.36 | 3.73 |
| 15 | 0.32 | 5.00 | 1.28 | 3.62 |
| 16 | 0.26 | 3.96 | 1.03 | 2.80 |
| 17 | 0.27 | 3.98 | 1.00 | 2.64 |
| 18 | 0.31 | 4.20 | 1.47 | 3.62 |
| 19 | 0.27 | 4.29 | 1.07 | 3.06 |
| 20 | 0.35 | 4.79 | 1.39 | 3.01 |
| 21 | 0.27 | 4.19 | 0.81 | 2.22 |
| 22 | 0.36 | 4.76 | 1.28 | 3.07 |
| 23 | 0.36 | 4.31 | 1.60 | 3.50 |
| 24 | 0.41 | 4.61 | 1.67 | 3.30 |
| 25 | 0.47 | 4.36 | 1.81 | 3.10 |
| 25-1 | 0.26 | 2.12 | 1.41 | 2.08 |
| 24-2 | 0.18 | 1.84 | 1.05 | 2.00 |
| **Panel B: By Rating** | | | | |
| AAA/AA | | | | |
| 1 | 0.10 | 1.55 | 0.11 | 0.30 |
| 5 | 0.15 | 2.85 | 0.36 | 1.14 |
| 5-1 | 0.05 | 0.70 | 0.25 | 0.66 |
| A | | | | |
| 1 | 0.25 | 3.20 | 0.78 | 1.92 |
| 5 | 0.39 | 4.52 | 1.52 | 3.22 |
| 5-1 | 0.15 | 1.75 | 0.74 | 1.71 |
| BBB | | | | |
| 1 | 0.20 | 2.07 | 0.54 | 1.38 |
| 5 | 0.36 | 5.13 | 1.15 | 2.91 |
| 5-1 | 0.15 | 2.51 | 0.61 | 1.97 |
| Below BBB | | | | |
| 1 | 0.17 | 1.62 | 0.54 | 0.92 |
| 5 | 0.55 | 5.37 | 2.27 | 4.09 |
| 5-1 | 0.38 | 3.55 | 1.72 | 2.91 |

spillover portfolios at $K = 1$. Both unadjusted (OLS) and adjusted (WLS) regression results show a similar pattern. The two factors, DEF and TERM, explain 18% of cross-sectional return variations across portfolios in the OLS regression, and default and term beta premiums are significant at least at the 5% level. Introducing the Fama–French three factors increases the adjusted $R^2$ to 21%, with the equity market return (MKT) significant at the 5% level.

Consistent with the finding of Elton et al. [2001], the Fama–French three factors help explain cross-sectional variations in bond returns. The equity market factors are helpful, possibly because both bonds and stocks are firms' claims on the value of the same underlying assets and thus share some common variations in returns. Another reason is that expected default loss of corporate bonds changes with equity price. As the equity value appreciates, default risk declines, which can induce a systematic factor that affects corporate bond returns.

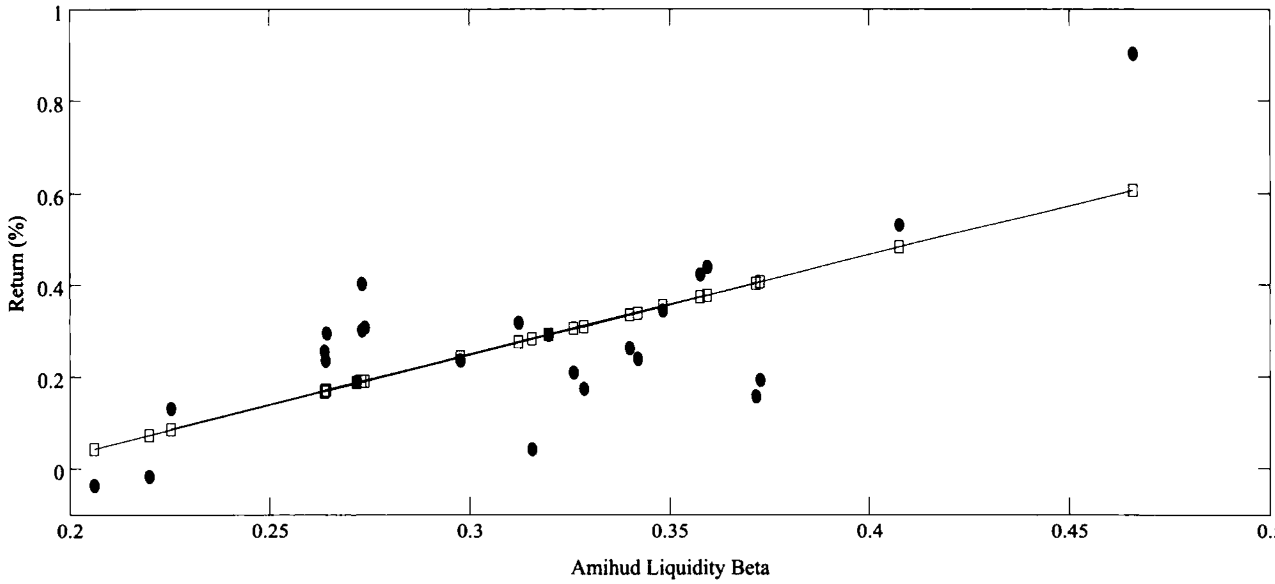
Adding the liquidity factor improves the adjusted $R^2$ to 29% when using the Amihud liquidity measure, and the liquidity risk price is significant at the 1% level. Results are similar when using the Pastor–Stambaugh measure as the liquidity factor. The coefficients of both Amihud and Pastor–Stambaugh liquidity betas are significant at the 1% level for both OLS and WLS regressions. Results strongly suggest that liquidity risk is priced in momentum spillover portfolio returns.

An important question is how much of the momentum spillover effect can be explained by the liquidity beta. Using the Amihud liquidity factor, the 25-1 liquidity beta spread is 0.26. Given the point estimate of 1.14 for the liquidity risk price in the WLS regression, this implies a liquidity spread of

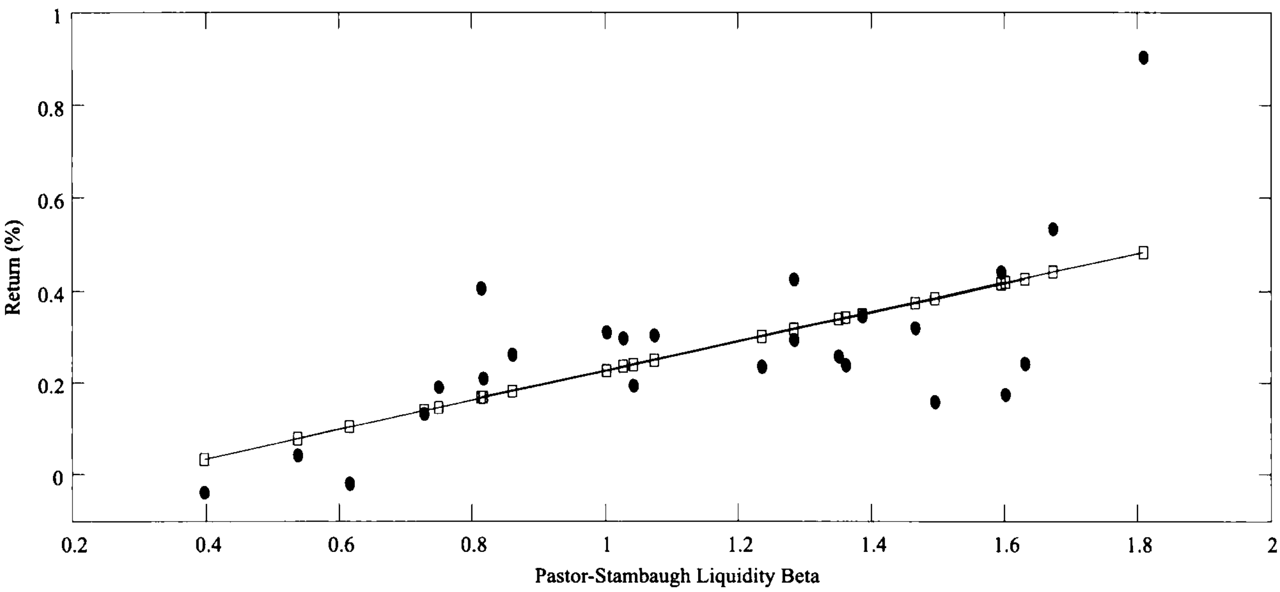
## EXHIBIT 6
### Relation between Bond Returns and Liquidity Betas of Equity Momentum Spillover Portfolios

Panel A plots the relation between excess returns and the Amihud liquidity betas, and Panel B plots that between excess returns and the Pastor–Stambaugh liquidity betas of 25 bond portfolios formed by past six-month stock returns. Liquidity betas are full-sample estimates, and *Return* in the vertical axis is mean excess returns of bond portfolios at $K = 1$. The sample period is from January 1994 to September 2009.

**Panel A: Relation between Return and Amihud Liquidity Beta**




**Panel B: Relation between Return and Pastor-Stambaugh Liquidity Beta**

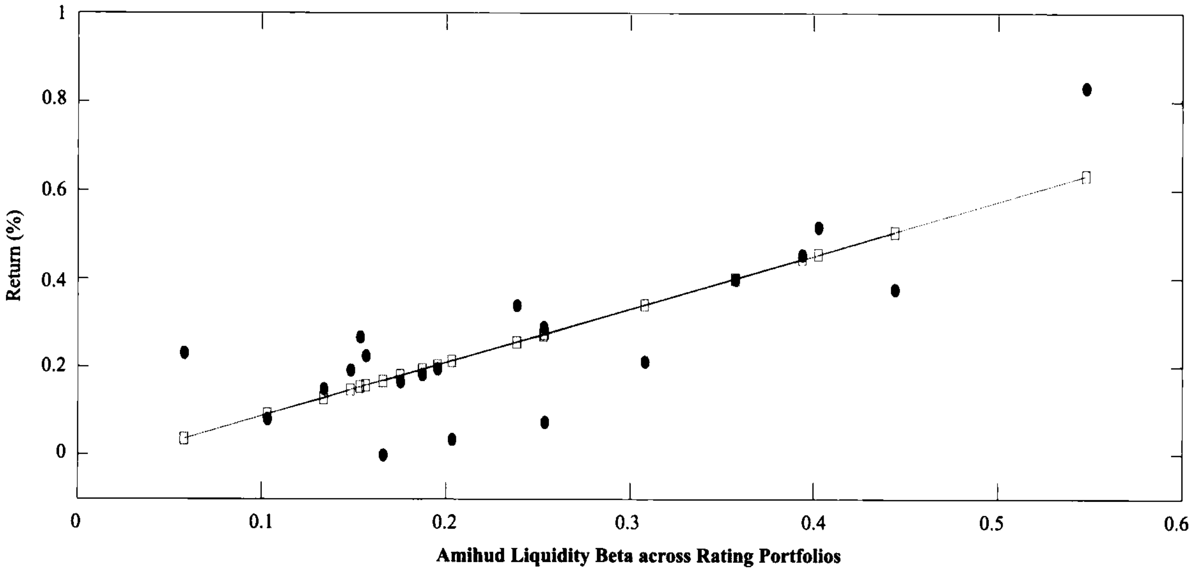


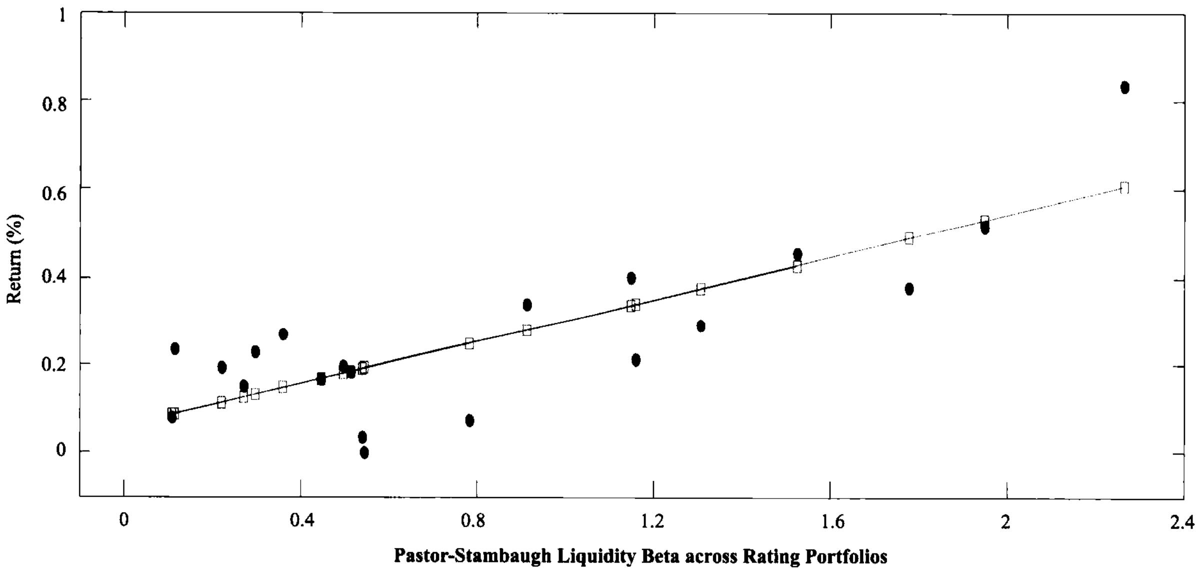

30 bps, which explains 32% of the return spread (94 bps) between portfolios 1 and 25. Similarly, the 24-2 liquidity beta spread is 0.18, which gives a liquidity spread of 21 bps that explains 38% of the return spread (55 bps) between portfolios 2 and 24. The unweighted OLS results give liquidity spreads of 39 and 27 bps, which explain 41% and 49% of the 25-1 and 24-2 portfolio returns, respectively. Thus, a sizable portion of the

# Exhibit 7

## Relation between Bond Returns and Liquidity Betas of Equity Momentum Spillover Portfolios by Rating

Panel A plots the relation between excess returns and the Amihud liquidity betas, and Panel B plots that between excess returns and the Pastor–Stambaugh liquidity betas of 20 bond portfolios formed by past-six-month stock returns for each rating category. Liquidity betas are full-sample estimates, and *Return* in the vertical axis is mean excess returns of bond portfolios at $K = 1$. The sample period is from January 1994 to September 2009.




momentum spillover return is explained by the liquidity risk premium.

Using the Pastor–Stambaugh liquidity factor, the liquidity beta spread between portfolios 1 and 25 is 1.41. Given the WLS estimate of 0.22 for the liquidity risk price, this implies a liquidity spread of 31 bps, which explains 33% of the return spread between portfolios 1 and 25. Similarly, the liquidity spread between portfolios

# Exhibit 8
## Asset Pricing Tests

This exhibit reports the cross-sectional test of asset pricing model $E[R_i] = \gamma_0 + \gamma\beta_i$, where $E[R_i]$ denotes the expected excess return of portfolio $i$, $\beta_i$ is a vector of factor loadings estimated from the first-step time-series regression, and $\gamma$ is a vector of premiums. Betas are estimated using the full sample, and the cross-sectional test is performed each month for the two-, five- and six-factor models and the six-factor model with bond characteristics.

Panels A and B report estimates of cross-sectional regressions of 25 momentum spillover portfolios with $t$ values in parentheses for $K = 1$ and 2, respectively. Panels C and D report estimates of cross-sectional regressions of 20 momentum spillover portfolios based on ratings for $K = 1$ and 2, respectively. $\hat{c}$ is the coefficient estimated by the Shanken [1992] method to adjust standard errors. Both ordinary least squares (OLS) and weighted least squares (WLS) regression results are reported. The result of the WLS regression uses variance of portfolio return residuals estimated from the factor model as weights, as suggested by Shanken and Zhou [2007]. The adjusted $R^2$ values of WLS regressions are calculated using the method of Kandel and Stambaugh [1995].

**Panel A: Asset Pricing Test of 25 Momentum Spillover Portfolios (K = 1)**

| Model | *Intercept* | *MKT* | *SMB* | *HML* | *DEF* | *TERM* | *LIQ* | *Ab_vol* | *Volatility* | *Size* | *Rating* | *Coupon* | *Age* | $\hat{c}$ | *Adj.R²* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *OLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | –0.91 | | | | 1.09 | 1.36 | | | | | | | | 1.85 | 0.18 |
| | (–3.18) | | | | (2.86) | (2.32) | | | | | | | | | |
| (2) Five-factor | –1.14 | 1.89 | 1.55 | 1.04 | 0.82 | 1.76 | | | | | | | | 2.30 | 0.21 |
| | (–3.61) | (2.07) | (1.45) | (1.04) | (2.43) | (3.18) | | | | | | | | | |
| (3) Amihud liquidity | –1.08 | –2.51 | 2.74 | 1.25 | 0.78 | 0.75 | 1.50 | | | | | | | 4.39 | 0.29 |
| | (–2.44) | (–1.85) | (1.94) | (0.95) | (2.19) | (1.08) | (2.89) | | | | | | | | |
| (4) Amihud liquidity | –1.45 | –3.37 | 2.12 | 0.56 | 0.30 | 1.45 | 1.33 | –0.02 | 0.05 | 0.03 | 0.02 | 0.09 | –0.05 | 4.18 | 0.39 |
| | (–2.04) | (–2.15) | (1.55) | (0.36) | (0.75) | (2.44) | (2.75) | (–0.29) | (1.71) | (0.11) | (1.25) | (2.78) | (–2.28) | | |
| (5) PS liquidity | –0.31 | –1.06 | 3.13 | –1.42 | 0.87 | 0.76 | 0.33 | | | | | | | 5.25 | 0.23 |
| | (–0.86) | (–0.80) | (2.00) | (–0.92) | (1.96) | (1.09) | (3.55) | | | | | | | | |
| (6) PS liquidity | –1.02 | –2.58 | 1.16 | –0.66 | 0.89 | 1.37 | 0.22 | –0.02 | 0.05 | 0.13 | 0.04 | 0.04 | –0.04 | 4.14 | 0.35 |
| | (–1.34) | (–1.70) | (0.78) | (–0.41) | (1.73) | (2.22) | (2.88) | (–0.27) | (1.71) | (0.58) | (2.31) | (1.24) | (–1.58) | | |
| *WLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | –0.57 | | | | 0.52 | 1.32 | | | | | | | | 0.97 | 0.13 |
| | (–2.81) | | | | (1.96) | (2.79) | | | | | | | | | |
| (2) Five-factor | –0.73 | 0.61 | 1.31 | 0.99 | 0.55 | 1.43 | | | | | | | | 1.42 | 0.17 |
| | (–3.12) | (0.78) | (1.50) | (1.12) | (1.97) | (3.12) | | | | | | | | | |
| (3) Amihud liquidity | –0.70 | –2.08 | 2.09 | 1.19 | 0.49 | 0.76 | 1.14 | | | | | | | 2.69 | 0.20 |
| | (–2.10) | (–1.88) | (1.97) | (1.16) | (1.94) | (1.33) | (3.24) | | | | | | | | |
| (4) Amihud liquidity | –1.30 | –3.26 | 1.67 | 0.72 | 0.23 | 1.34 | 0.72 | –0.02 | 0.05 | 0.02 | 0.03 | 0.08 | –0.05 | 2.47 | 0.30 |
| | (–2.31) | (–2.62) | (1.60) | (0.59) | (0.69) | (2.76) | (2.07) | (–0.18) | (1.76) | (0.08) | (1.44) | (2.51) | (–2.15) | | |
| (5) PS liquidity | –0.23 | –1.30 | 2.52 | –0.82 | 0.57 | 0.90 | 0.22 | | | | | | | 2.96 | 0.18 |
| | (–0.84) | (–1.20) | (2.15) | (–0.70) | (1.78) | (1.55) | (3.73) | | | | | | | | |
| (6) PS liquidity | –0.86 | –2.68 | 0.95 | –0.28 | 0.74 | 1.28 | 0.18 | –0.01 | 0.05 | 0.13 | 0.04 | 0.02 | –0.03 | 3.24 | 0.27 |
| | (–1.29) | (–2.00) | (0.75) | (–0.20) | (1.67) | (2.32) | (2.77) | (–0.08) | (1.62) | (0.61) | (2.46) | (0.77) | (–1.14) | | |

## EXHIBIT 8 (Continued)

**Panel B: Asset Pricing Test of 25 Momentum Spillover Portfolios (K = 2)**

| Model | *Intercept* | *MKT* | *SMB* | *HML* | *DEF* | *TERM* | *LIQ* | *Ab_vol* | *Volatility* | *Size* | *Rating* | *Coupon* | *Age* | $\hat{c}$ | *Adj.R²* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *OLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | –0.64 | | | | 0.84 | 1.01 | | | | | | | | 1.06 | 0.19 |
| | (–1.95) | | | | (2.12) | (1.94) | | | | | | | | | |
| (2) Five-factor | –0.77 | 3.68 | –0.39 | 0.53 | 1.22 | 0.96 | | | | | | | | 1.83 | 0.34 |
| | (–2.03) | (2.80) | (–0.32) | (0.48) | (1.92) | (1.73) | | | | | | | | | |
| (3) Amihud liquidity | –1.00 | 2.42 | 2.00 | 0.42 | 1.14 | 1.08 | 0.42 | | | | | | | 2.00 | 0.35 |
| | (–2.32) | (1.72) | (1.52) | (0.41) | (1.92) | (1.69) | (1.87) | | | | | | | | |
| (4) Amihud liquidity | –0.91 | 1.50 | 0.75 | 0.53 | 0.86 | 0.88 | 0.45 | –0.04 | 0.01 | –0.19 | 0.01 | 0.03 | –0.01 | 1.12 | 0.41 |
| | (–2.04) | (1.44) | (0.69) | (0.67) | (1.79) | (1.95) | (1.67) | (–0.45) | (0.18) | (–0.87) | (0.44) | (1.00) | (–0.32) | | |
| (5) PS liquidity | –0.48 | 3.35 | –0.41 | 0.42 | 0.82 | 0.82 | 0.09 | | | | | | | 1.30 | 0.35 |
| | (–1.23) | (2.42) | (–0.37) | (0.42) | (1.79) | (1.45) | (1.87) | | | | | | | | |
| (6) PS liquidity | –0.10 | 1.64 | –1.01 | 0.46 | 0.53 | 0.85 | 0.08 | –0.02 | 0.01 | –0.20 | 0.01 | 0.04 | 0.01 | 0.80 | 0.42 |
| | (–0.25) | (1.21) | (–0.97) | (0.50) | (1.17) | (1.80) | (1.76) | (–0.23) | (0.17) | (–0.90) | (0.68) | (1.30) | (0.02) | | |
| *WLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | –0.32 | | | | 0.52 | 0.73 | | | | | | | | 0.48 | 0.14 |
| | (–1.27) | | | | (1.86) | (1.68) | | | | | | | | | |
| (2) Five-factor | –0.57 | 2.91 | –0.18 | 0.58 | 0.94 | 0.85 | | | | | | | | 1.20 | 0.24 |
| | (–1.78) | (2.84) | (–0.18) | (0.59) | (1.85) | (1.69) | | | | | | | | | |
| (3) Amihud liquidity | –0.78 | 1.99 | 1.72 | 0.51 | 0.97 | 1.03 | 0.37 | | | | | | | 1.59 | 0.25 |
| | (–2.05) | (1.63) | (1.48) | (0.52) | (1.92) | (1.72) | (1.79) | | | | | | | | |
| (4) Amihud liquidity | –0.86 | 0.95 | 0.80 | 0.44 | 0.72 | 0.89 | 0.43 | –0.03 | 0.01 | –0.17 | 0.01 | 0.04 | –0.01 | 0.97 | 0.32 |
| | (–2.05) | (0.96) | (0.79) | (0.52) | (1.62) | (1.94) | (1.79) | (–0.41) | (0.31) | (–0.80) | (0.41) | (1.20) | (–0.21) | | |
| (5) PS liquidity | –0.30 | 2.24 | –0.15 | 0.55 | 0.73 | 0.67 | 0.07 | | | | | | | 0.79 | 0.25 |
| | (–0.96) | (2.04) | (–0.17) | (0.63) | (1.86) | (1.42) | (1.80) | | | | | | | | |
| (6) PS liquidity | –0.19 | 1.09 | –0.65 | 0.50 | 0.50 | 0.80 | 0.07 | –0.01 | 0.02 | –0.15 | 0.01 | 0.06 | 0.01 | 0.65 | 0.32 |
| | (–0.52) | (0.87) | (–0.67) | (0.57) | (1.23) | (1.82) | (1.78) | (–0.13) | (0.41) | (–0.72) | (0.49) | (1.71) | (0.27) | | |

## EXHIBIT 8 (Continued)

**Panel C: Asset Pricing Test of 20 Rating Momentum Spillover Portfolios (K = 1)**

| Model | *Intercept* | *MKT* | *SMB* | *HML* | *DEF* | *TERM* | *LIQ* | *Ab_vol* | *Volatility* | *Size* | *Rating* | *Coupon* | *Age* | $\hat{c}$ | *Adj.*$R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *OLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | –0.76 | | | | 1.41 | 0.93 | | | | | | | | 1.86 | 0.35 |
| | (–3.15) | | | | (3.81) | (2.35) | | | | | | | | | |
| (2) Five-factor | –0.45 | 1.19 | –4.03 | 3.20 | 1.52 | 0.39 | | | | | | | | 2.90 | 0.42 |
| | (–1.52) | (0.62) | (–2.16) | (1.94) | (2.65) | (0.95) | | | | | | | | | |
| (3) Amihud liquidity | –0.28 | –2.07 | –0.82 | 1.52 | 1.18 | 0.09 | 1.27 | | | | | | | 2.55 | 0.47 |
| | (–1.01) | (–1.16) | (–0.68) | (1.20) | (1.89) | (0.25) | (4.51) | | | | | | | | |
| (4) Amihud liquidity | –1.43 | –2.70 | –0.15 | 2.31 | 1.30 | 0.41 | 1.10 | 0.23 | 0.03 | 0.09 | –0.02 | 0.11 | 0.01 | 2.98 | 0.59 |
| | (–1.71) | (–1.20) | (–0.07) | (1.48) | (1.38) | (0.85) | (3.32) | (1.70) | (0.77) | (0.38) | (–1.64) | (2.27) | (0.33) | | |
| (5) PS liquidity | –0.76 | –2.84 | 0.35 | 0.08 | 1.75 | 0.53 | 0.33 | | | | | | | 6.42 | 0.47 |
| | (–1.45) | (–1.20) | (0.21) | (0.04) | (2.11) | (0.72) | (4.15) | | | | | | | | |
| (6) PS liquidity | –1.60 | –4.03 | 1.59 | 2.46 | 1.77 | 0.73 | 0.31 | 0.17 | 0.01 | 0.20 | –0.02 | 0.08 | 0.01 | 7.60 | 0.59 |
| | (–1.12) | (–1.14) | (0.60) | (0.61) | (1.20) | (0.68) | (2.88) | (1.56) | (0.27) | (0.81) | (–1.65) | (1.45) | (0.19) | | |
| *WLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | –0.34 | | | | 0.86 | 0.57 | | | | | | | | 0.69 | 0.29 |
| | (–1.98) | | | | (2.74) | (1.84) | | | | | | | | | |
| (2) Five-factor | –0.03 | 0.41 | –3.43 | 3.81 | 0.84 | 0.28 | | | | | | | | 1.93 | 0.36 |
| | (–0.10) | (0.25) | (–2.28) | (2.85) | (1.88) | (0.80) | | | | | | | | | |
| (3) Amihud liquidity | –0.31 | –1.67 | –1.65 | 2.85 | 1.31 | 0.20 | 1.03 | | | | | | | 2.44 | 0.40 |
| | (–1.13) | (–0.96) | (–1.32) | (2.34) | (2.16) | (0.60) | (4.05) | | | | | | | | |
| (4) Amihud liquidity | –1.33 | –2.08 | –0.44 | 2.81 | 1.30 | 0.43 | 0.95 | 0.24 | 0.03 | 0.04 | –0.02 | 0.11 | 0.01 | 2.60 | 0.53 |
| | (–1.74) | (–1.06) | (–0.25) | (1.93) | (1.51) | (0.94) | (3.12) | (1.93) | (0.73) | (–0.52) | (–1.61) | (2.27) | (0.24) | | |
| (5) PS liquidity | –0.40 | –2.03 | –1.24 | 2.00 | 1.26 | 0.35 | 0.24 | | | | | | | 3.40 | 0.39 |
| | (–0.98) | (–1.07) | (–0.88) | (1.36) | (1.82) | (0.61) | (4.61) | | | | | | | | |
| (6) PS liquidity | –1.42 | –3.77 | 0.92 | 2.10 | 1.45 | 0.67 | 0.27 | 0.15 | 0.02 | 0.18 | –0.02 | 0.08 | –0.01 | 5.60 | 0.52 |
| | (–1.22) | (–1.22) | (0.42) | (0.69) | (1.15) | (0.75) | (3.00) | (1.44) | (0.49) | (0.79) | (–1.53) | (1.52) | (–0.14) | | |

## Exhibit 8 (Continued)

**Panel D: Asset Pricing Test of 20 Rating Momentum Spillover Portfolios (K = 2)**

| Model | *Intercept* | *MKT* | *SMB* | *HML* | *DEF* | *TERM* | *LIQ* | *Ab_vol* | *Volatility* | *Size* | *Rating* | *Coupon* | *Age* | $\hat{c}$ | $Adj.R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *OLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | 0.05 | | | | 0.65 | 0.13 | | | | | | | | 0.24 | 0.31 |
| | (0.43) | | | | (2.52) | (0.52) | | | | | | | | | |
| (2) Five-factor | –0.66 | –0.29 | –2.86 | 3.99 | 1.52 | 0.68 | | | | | | | | 3.02 | 0.41 |
| | (–1.59) | (–0.18) | (–1.82) | (1.95) | (2.27) | (1.27) | | | | | | | | | |
| (3) Amihud liquidity | –0.33 | –1.58 | –0.14 | 2.20 | 0.91 | 0.60 | 0.56 | | | | | | | 1.75 | 0.45 |
| | (–0.89) | (–1.59) | (–0.14) | (1.67) | (2.13) | (1.05) | (2.49) | | | | | | | | |
| (4) Amihud liquidity | –1.48 | –1.70 | 0.08 | 2.18 | 1.33 | 1.12 | 0.66 | 0.18 | 0.07 | 0.04 | –0.02 | 0.17 | –0.03 | 2.94 | 0.57 |
| | (–1.55) | (–0.64) | (0.04) | (1.05) | (1.72) | (1.38) | (1.83) | (1.46) | (1.56) | (0.15) | (–1.65) | (3.31) | (–1.04) | | |
| (5) PS liquidity | 0.08 | –1.67 | –0.37 | 2.15 | 0.65 | 0.19 | 0.09 | | | | | | | 1.02 | 0.45 |
| | (0.34) | (–1.48) | (–0.37) | (1.99) | (1.96) | (0.48) | (3.91) | | | | | | | | |
| (6) PS liquidity | –0.78 | –0.91 | –1.78 | 1.71 | 0.26 | 0.17 | 0.07 | 0.38 | 0.09 | 0.02 | –0.01 | 0.12 | –0.01 | 0.57 | 0.54 |
| | (–1.49) | (–0.62) | (–1.33) | (1.10) | (0.63) | (0.36) | (1.70) | (2.80) | (1.92) | (0.08) | (–0.49) | (2.35) | (–0.34) | | |
| *WLS regressions:* | | | | | | | | | | | | | | | |
| (1) Two-factor | 0.12 | | | | 0.54 | 0.06 | | | | | | | | 0.16 | 0.28 |
| | (1.10) | | | | (2.14) | (0.24) | | | | | | | | | |
| (2) Five-factor | –0.30 | –1.17 | –0.90 | 2.95 | 1.27 | 0.22 | | | | | | | | 1.66 | 0.36 |
| | (–1.04) | (–0.89) | (–0.86) | (2.02) | (2.40) | (0.55) | | | | | | | | | |
| (3) Amihud liquidity | –0.34 | –2.61 | 0.36 | 1.86 | 0.86 | 0.71 | 0.54 | | | | | | | 1.87 | 0.39 |
| | (–0.92) | (–1.71) | (0.33) | (1.36) | (1.87) | (1.27) | (3.00) | | | | | | | | |
| (4) Amihud liquidity | –1.19 | –1.44 | 0.97 | 1.53 | 1.11 | 0.94 | 0.58 | 0.19 | 0.04 | 0.01 | –0.02 | 0.16 | –0.03 | 2.21 | 0.51 |
| | (–1.37) | (–0.66) | (0.54) | (0.85) | (1.72) | (1.33) | (1.81) | (1.56) | (0.86) | (0.04) | (–1.61) | (3.02) | (–1.02) | | |
| (5) PS liquidity | –0.01 | –1.97 | 0.10 | 2.00 | 0.69 | 0.34 | 0.09 | | | | | | | 1.22 | 0.38 |
| | (0.06) | (–1.70) | (0.10) | (1.84) | (2.00) | (0.84) | (4.03) | | | | | | | | |
| (6) PS liquidity | –0.75 | –1.34 | –0.56 | 1.12 | 0.31 | 0.19 | 0.08 | 0.35 | 0.06 | –0.01 | –0.02 | 0.13 | –0.01 | 0.48 | 0.49 |
| | (–1.40) | (–1.00) | (–0.47) | (0.81) | (0.78) | (0.45) | (1.82) | (2.71) | (1.41) | (–0.03) | (–0.97) | (2.43) | (–0.11) | | |

2 and 24 is 23 bps, which explains 42% of the return spread between portfolios 2 and 24. The unadjusted OLS results give higher liquidity spread estimates of 46 and 35 bps, which explain 50% and 63% of return spreads. Again, the liquidity beta appears to be an economically significant determinant of momentum spillover returns. Based on the overall average of regressions for both liquidity measures, liquidity risk explains about 40% of the momentum spillover return at $K = 1$.

We also formed 25 momentum spillover portfolios based on more conservative return estimates at $K = 2$. For brevity, we summarize only key results in the first-step time-series regression. Monthly return spreads of 25-1 and 24-2 portfolios at $K = 2$ are 51 and 26 bps. Liquidity betas of the zero-investment 25-1 and 24-2 portfolios are 0.33 and 0.28, respectively, using the Amihud liquidity factor, and 1.79 and 1.51, using the Pastor–Stambaugh liquidity factor, all significant at the 1% level.

Panel B of Exhibit 8 reports results of cross-sectional regression tests based on portfolio returns and beta estimates at $K = 2$. The pattern is similar to the cross-sectional regression of portfolio returns at $K = 1$, although the significance of coefficients is reduced. For the OLS and WLS regressions, both Pastor–Stambaugh and Amihud liquidity betas are significant at the 10% level. Using the Amihud liquidity factor, the point estimate of 0.37 for the liquidity beta coefficient in the WLS regression implies a liquidity spread of 12 bps, which explains 24% of the return spread (51 bps) between portfolios 1 and 25. The 24-2 liquidity beta spread of 0.28 gives a liquidity spread of 10 bps, which explains 39% of the return difference (26 bps) between portfolios 2 and 24. By contrast, the OLS results give liquidity spread estimates of 14 and 12 bps, which explain 27% and 44%, respectively, of the 25-1 and 24-2 portfolio return spreads at $K = 2$.

Using the Pastor–Stambaugh liquidity factor, the point estimate of 0.07 for the coefficient of the liquidity beta in the WLS regression implies a liquidity spread of 13 bps, which explains 25% of the return spread between portfolios 1 and 25. The 24-2 liquidity spread is 11 bps, which explains 40% of the return difference between portfolios 2 and 24. The OLS results give liquidity spread estimates of 16 and 14 bps, which explain 32% and 52% of the 25-1 and 24-2 portfolios return spreads, respectively. Again, the evidence shows that liquidity risk is important in the pricing of momentum spillover portfolio returns. Results appear to be robust to microstructure effects.

### Liquidity Risk Pricing across Ratings

We next examine the effect of liquidity risk on equity momentum spillover returns for bonds with different ratings. Panel C of Exhibit 8 shows results of the cross-sectional regression test using the 20 portfolios based on returns at $K = 1$. The goodness-of-fit and estimation efficiency improves significantly by using rating portfolios, as indicated by higher adjusted $R^2$ and $t$ values. The two factors, DEF and TERM, explain 35% of cross-sectional return variations in the OLS regression. Default and term betas are significant at the 1% and 5% levels in the OLS regression. Introducing the Fama–French three factors increases the adjusted $R^2$ to 42% in the OLS regression. Adding the liquidity factor further increases the adjusted $R^2$ to 47%. The coefficient of the liquidity beta is significant at the 1% level for both Amihud and Pastor–Stambaugh liquidity measures, regardless of the OLS or WLS regression.

Using the Amihud liquidity measure, coefficient estimates of WLS regressions give liquidity spreads for the zero-investment 5-1 portfolios of 5, 14, 16, and 39 bps for bonds with ratings of AAA/AA, A, BBB, and below BBB, respectively, which explain 28%, 38%, 44%, and 47% of the return spread between portfolios 1 (stock loser) and 5 (stock winner) in each rating category. Using the Pastor–Stambaugh liquidity measure, liquidity spreads of the 5-1 portfolios are 6, 18, 15, and 41 bps for bonds with ratings AAA/AA, A, BBB, and below BBB, respectively, which explain 32%, 47%, 40%, and 50% of the return spread between portfolios 1 and 5 in each rating category.

By contrast, the OLS results give liquidity spread estimates of 6, 18, 20, and 49 bps, which explain 34%, 47%, 54%, and 58% of the 5-1 portfolio return spreads when using the Amihud measure. The OLS liquidity spread estimates are 8, 25, 20, and 57 bps, which explain 44%, 64%, 55%, and 68% of the 5-1 portfolio return spreads when using the Pastor–Stambaugh measure. Overall, results show that on average liquidity risk explains a little over 40% of momentum spillover returns for investment-grade bonds and 55% of returns for speculative-grade bonds. The liquidity beta explains a higher proportion of the momentum spillover returns for lower-grade bonds.

Panel D of Exhibit 8 shows cross-sectional regression results for bond portfolio returns at $K = 2$. The liquidity beta continues to be significant at the 1% level for WLS regressions. Using the Amihud liquidity measure, liquidity spreads of the 5-1 portfolios are 2, 8, 10, and 21 bps for bonds with ratings of AAA/AA, A, BBB, and below BBB, respectively, which explain 23%, 57%, 57%, and 43% of the return spread between portfolios 5 and 1 in each rating category. Using the Pastor–Stambaugh liquidity factor, liquidity spreads of the 5-1 portfolios are 2, 6, 9, and 18 bps for bonds with ratings AAA/AA, A, BBB, and below BBB, respectively, which explain 17%, 43%, 47%, and 36% of the return spread between portfolios 1 and 5 in each rating category. The unadjusted OLS result gives higher liquidity spreads for the model using the Amihud measure.

In summary, there is strong evidence that liquidity risk is priced in the cross section of momentum spillover portfolio returns. The liquidity beta explains an economically significant portion of momentum spillover returns, and the liquidity risk premium accounts for a higher proportion of portfolio returns of lower-grade bonds. Results show that liquidity risk explains the variation in momentum spillover effects across ratings.

## Alternative Explanations

The preceding analysis shows that the liquidity risk factor explains substantial cross-sectional variations in momentum spillover portfolio returns. However, the literature has suggested several other factors that can explain stock momentum returns. It is unclear how the liquidity risk factor fares against these factors in the cross-sectional regression of momentum spillover returns. In this section, we examine the robustness of our results with alternative variables in the literature.

The first alternative variable we consider is trading volume. Trading volume is related to cost of trading or liquidity, information asymmetries, and uncertainty about a firm's future performance. The equity momentum literature has suggested that behavior biases generate excess trading volume (Odean [1998]; Gervais and Odean [2001]; Scheinkman and Xiong [2003]). There is a close relationship between trading volume and overconfidence. Overconfident investors trade more, as they overestimate the precision of their information. We can examine whether this behavioral factor may explain the momentum spillover returns in the cross section using volume as a proxy (see also Chiu, Titman, and Wei [2010]). In our empirical investigation, we calculate abnormal volume, which is the percentage of deviation of the volume in the preceding year from the average volume for the entire sample period, to capture the volume effect.

The second important variable is return volatility. Previous studies have suggested that trading by investors with overconfidence and self-attribution bias leads to excess volatility (Odean [1998]; Statman et al. [2006]; Glaser and Weber [2009]). Chui, Titman, and Wei [2010]) find that individualistic investors are subject to more bias, and their trading has a strong positive effect on volatility. These investors tend to make investment choices that generate momentum profits. We examine whether return volatility is a better predictor of momentum spillover returns than other systematic factors.

Moreover, the literature has suggested that bond characteristics such as issue size, coupon rate, age, and ratings can affect cross-sectional variations in bond returns (see Longstaff, Mithal, and Neis [2005]). Issue size and age are commonly used measures of bond liquidity. Younger bonds with a larger issue size are more actively traded and have higher liquidity. Since trading costs for these bonds are lower, momentum strategies may be more profitable for these bonds (Korajczyk and Sadka [2004]; Lesmond et al. [2004]). Coupon may proxy for the tax effect, as the interest income of corporate bonds is taxable. Credit quality is related to the momentum spillover. As shown in the preceding analysis, bonds with lower ratings have higher momentum spillover. Finally, we note that volume and volatility can also proxy for liquidity. High volume and low volatility are typically associated with high liquidity.

We include these variables in the cross-sectional regression to check the robustness of our results to alternative explanations. Exhibit 8 (specifications 4 and 6) reports results of cross-sectional regressions that incorporate these variables. For $K = 1$ in Panels A and C, results show both the Pastor–Stambaugh and Amihud liquidity betas remain highly significant for both unadjusted (OLS) and adjusted (WLS) regressions after controlling for the effects of alternative variables. Results strongly indicate that the liquidity beta is important above and beyond the effects of alternative variables. Among the control variables, coupon and age are significant at the 5% level when the Amihud measure is used as the liquidity factor. The rating is significant at the 5% level when using the Pastor–Stambaugh measure as the liquidity factor. Volatility is significant at the 10% level in both OLS and WLS regressions (Panel A).

In the regression of rating spillover portfolio returns with $K = 1$ (Panel C), volume is significant at the 10% level when using the Amihud liquidity measure. Results show some evidence for the effect of behavioral factors on the momentum spillover. For $K = 2$, the liquidity beta remains significant after incorporating alternative variables. The coupon rate is significant at the 1% level in the rating spillover portfolio return regression and at the 10% level in the momentum spillover portfolio regression. Volume is significant at the 1% level (Panel D) when using the Pastor–Stambaugh liquidity measure in the rating spillover portfolio regression.

Overall, the evidence strongly supports the hypothesis that the liquidity risk factor is priced in momentum spillover portfolio returns. Liquidity risk explains a significant portion of the cross-sectional variation in portfolio returns. The effect of liquidity risk remains significantly positive even after controlling for the effects of behavioral factors and bond characteristics.

### Robustness Check for Cross-Sectional Regression Tests

In our cross-sectional tests, $t$ values and adjusted $R^2$ are used to evaluate the importance of the liquidity factor. Lewellen, Nagel, and Shanken [2010] argue that when returns of test portfolios have a strong covariance structure like SMB-HML or TERM-DEF portfolios, loading on a proposed factor is likely to line up with expected returns, as long as that factor is correlated with the common sources of variations in returns but not with the idiosyncratic residuals of portfolios. In such a case, a factor like liquidity may have a significant $t$-statistic and high cross-sectional $R^2$ in-sample, even though it explains little of the cross-sectional variation in true expected returns. To avoid this spurious regression, they suggest several ways to resolve the problem, which include using portfolios sorted by factor loadings or characteristics in the cross-sectional tests, or imposing a theoretical restriction on the risk premium (i.e., setting the premium on a factor portfolio equal to its average excess return) instead of estimating it as a free parameter.

In the preceding cross-sectional tests, we used portfolios sorted by a bond characteristic (rating) and found that the results remained strong. This should provide some support for the cross-sectional test results. For robustness, we tried another detective method, suggested by Lewellen et al. [2010], by imposing the restriction that the risk premia of the Fama–French three factors and term and default factors in the cross-sectional test equal the average excess returns of portfolios formed by these factors. This approach was also used by Pastor and Stambaugh [2003] in the test of liquidity risk pricing in stock returns.

Exhibit 9 reports results of cross-sectional tests, which impose the theoretical restrictions on risk premia of the Fama–French three factors, and term and default factors. For brevity, we focus on the estimates for the liquidity risk and characteristic variable. Results show that the restrictions have little impact on our inference. If anything, the liquidity factor becomes even more significant after imposing restrictions on the risk premia of factors. All estimates of liquidity risk price are significant at the 1% level in the cross-sectional tests of momentum spillover portfolios (Panels A and B) and rating momentum portfolios (Panels C and D) for $K = 1, 2$, regardless of using OLS or WLS regressions. There is no evidence of spurious regressions. Results strongly suggest that the liquidity risk is priced in the momentum spillover portfolio returns.

## MOMENTUM SPILLOVERS IN DIFFERENT STATES

### Regime-Switching Regressions

Results in the preceding section show that the liquidity factor plays a significant role in equity momentum spillover. Næs, Skjeltorp, and Ødegaard [2011] find a strong relation between stock market liquidity and the business cycle. Together, these suggest that market liquidity and economic conditions can affect the efficacy of momentum spillover strategies. To gain further insight into the relation between liquidity risk and the equity momentum spillover, we examine the performance of momentum spillover strategies and the response of these strategies to different economic conditions.

To investigate the varying relation between liquidity risk and the equity momentum spillover, we use regime-switching regressions. We fit the data to a regime-switching model that allows for two distinct states in the mean and variance of portfolio returns. Using this approach, we can infer from the observed data the favorable and unfavorable latent states. We estimate the following regime-switching model:

## Exhibit 9

### Robust Cross-Sectional Regression Tests

This exhibit reports the cross-sectional test of asset pricing model $E[R_i] = \gamma_0 + \gamma\beta_i$, where $E[R_i]$ denotes the expected excess return of portfolio $i$, $\beta_i$ is a vector of factor loadings estimated from the first-step time-series regression, and $\gamma$ is a vector of premiums. Following Pastor and Stambaugh [2003] and Lewellen, Nagel, and Shanken [2010], the risk premiums of MKT, HML, SMB, DEF, and TERM factors (traded factors) are set equal to their mean portfolio returns.

Panels A and B report estimates of cross-sectional regressions of 25 momentum spillover portfolios, with $t$ values in parentheses for holding periods at $K = 1$ and 2, respectively. Panels C and D report estimates of cross-sectional regressions of 20 momentum spillover portfolios based on ratings for $K = 1$ and 2, respectively. Eqn-007. eps is the coefficient estimated by the Shanken [1992] method to adjust standard errors. Both ordinary least squares (OLS) and weighted least squares (WLS) regression results are reported. The result of WLS regression uses variance of portfolio return residuals estimated from the factor model as weights, as suggested by Shanken and Zhou [2007]. The adjusted $R^2$ values of WLS regressions are calculated using the method of Kandel and Stambaugh [1995].

| Model | *Intercept* | *LIQ* | *Ab_vol* | *Volatility* | *Size* | *Rating* | *Coupon* | *Age* | $\hat{c}$ | *Adj.R²* |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Asset Pricing Test of 25 Momentum Spillover Portfolios (K = 1)** | | | | | | | | | | |
| *OLS regressions:* | | | | | | | | | | |
| Amihud liquidity | −0.44 | 1.66 | | | | | | | 3.02 | 0.07 |
| | (−2.08) | (4.00) | | | | | | | | |
| Amihud liquidity | −0.79 | 0.98 | 0.01 | 0.01 | 0.04 | 0.03 | 0.08 | −0.03 | 1.07 | 0.33 |
| | (−2.43) | (3.57) | (0.19) | (0.06) | (0.18) | (1.78) | (3.29) | (−1.86) | | |
| PS liquidity | 0.14 | 0.27 | | | | | | | 2.37 | 0.06 |
| | (0.91) | (4.16) | | | | | | | | |
| PS liquidity | −0.23 | 0.20 | 0.01 | −0.01 | 0.10 | 0.04 | 0.05 | −0.03 | 1.28 | 0.30 |
| | (−0.65) | (4.29) | (0.04) | (−0.39) | (0.47) | (2.29) | (1.82) | (−1.74) | | |
| *WLS regressions:* | | | | | | | | | | |
| Amihud liquidity | −0.26 | 1.27 | | | | | | | 1.78 | 0.03 |
| | (−1.57) | (3.74) | | | | | | | | |
| Amihud liquidity | −0.64 | 1.07 | −0.02 | 0.01 | 0.05 | 0.03 | 0.06 | −0.02 | 1.26 | 0.25 |
| | (−1.91) | (4.22) | (−0.31) | (0.03) | (0.27) | (1.83) | (2.12) | (−1.00) | | |
| PS liquidity | 0.13 | 0.19 | | | | | | | 1.16 | 0.04 |
| | (1.06) | (4.33) | | | | | | | | |
| PS liquidity | −0.17 | 0.16 | −0.02 | −0.01 | 0.13 | 0.04 | 0.03 | −0.03 | 0.83 | 0.24 |
| | (0.56) | (4.30) | (−0.32) | (−0.37) | (0.62) | (2.19) | (1.04) | (−1.67) | | |
| **Panel B: Asset Pricing Test of 25 Momentum Spillover Portfolios (K = 2)** | | | | | | | | | | |
| *OLS regressions:* | | | | | | | | | | |
| Amihud liquidity | −0.12 | 0.82 | | | | | | | 0.75 | 0.06 |
| | (−1.01) | (3.63) | | | | | | | | |
| Amihud liquidity | −0.35 | 0.54 | −0.03 | 0.03 | −0.32 | 0.01 | 0.07 | −0.01 | 0.34 | 0.36 |
| | (−1.33) | (3.53) | (−0.37) | (0.83) | (−1.52) | (0.08) | (2.31) | (−0.78) | | |
| PS liquidity | −0.03 | 0.15 | | | | | | | 0.64 | 0.09 |
| | (−0.26) | (3.84) | | | | | | | | |
| PS liquidity | −0.37 | 0.12 | −0.02 | 0.02 | −0.19 | 0.01 | 0.07 | 0.01 | 0.48 | 0.37 |
| | (−1.29) | (3.70) | (−0.35) | (0.70) | (−0.91) | (0.75) | (2.34) | (0.38) | | |
| *WLS regressions:* | | | | | | | | | | |
| Amihud liquidity | −0.05 | 0.47 | | | | | | | 0.27 | 0.04 |
| | (−0.21) | (5.16) | | | | | | | | |
| Amihud liquidity | −0.28 | 0.44 | −0.05 | 0.03 | −0.27 | −0.01 | 0.07 | −0.01 | 0.24 | 0.25 |
| | (−1.14) | (3.49) | (−0.74) | (1.01) | (−1.30) | (−0.07) | (2.43) | (−0.61) | | |
| PS liquidity | 0.01 | 0.10 | | | | | | | 0.34 | 0.08 |
| | (0.10) | (3.25) | | | | | | | | |
| PS liquidity | −0.37 | 0.09 | −0.05 | 0.02 | −0.16 | 0.01 | 0.08 | 0.01 | 0.28 | 0.27 |
| | (−2.45) | (3.18) | (−0.79) | (0.69) | (−0.81) | (0.50) | (2.71) | (0.28) | | |

## Exhibit 9 (*Continued*)

**Panel C: Asset Pricing Test of 20 Rating Momentum Spillover Portfolios (K = 1)**

| Model | *Intercept* | *LIQ* | *Ab_vol* | *Volatility* | *Size* | *Rating* | *Coupon* | *Age* | $\hat{c}$ | *Adj.*$R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *OLS regressions:* | | | | | | | | | | |
| Amihud liquidity | –0.15 | 1.12 | | | | | | | 1.38 | 0.15 |
| | (–1.31) | (4.34) | | | | | | | | |
| Amihud liquidity | –0.77 | 1.10 | 0.06 | –0.01 | 0.48 | –0.01 | 0.08 | 0.01 | 1.36 | 0.57 |
| | (–1.68) | (5.85) | (0.60) | (–0.18) | (2.36) | (–0.64) | (1.93) | (0.70) | | |
| PS liquidity | 0.14 | 0.26 | | | | | | | 2.15 | 0.07 |
| | (1.00) | (6.19) | | | | | | | | |
| PS liquidity | –0.47 | 0.20 | 0.12 | –0.01 | 0.60 | 0.02 | 0.06 | 0.01 | 1.28 | 0.55 |
| | (–1.07) | (5.76) | (1.40) | (–0.28) | (3.05) | (1.78) | (1.53) | (0.17) | | |
| *WLS regressions:* | | | | | | | | | | |
| Amihud liquidity | –0.08 | 0.83 | | | | | | | 0.77 | 0.13 |
| | (–0.79) | (3.45) | | | | | | | | |
| Amihud liquidity | –0.75 | 0.97 | 0.10 | –0.01 | 0.39 | –0.01 | 0.08 | 0.02 | 1.04 | 0.43 |
| | (–1.78) | (5.73) | (0.98) | (0.09) | (1.99) | (–0.75) | (2.07) | (0.85) | | |
| PS liquidity | 0.12 | 0.21 | | | | | | | 1.41 | 0.02 |
| | (1.00) | (6.99) | | | | | | | | |
| PS liquidity | –0.50 | 0.17 | 0.12 | 0.01 | 0.55 | 0.02 | 0.06 | 0.01 | 0.93 | 0.41 |
| | (–1.28) | (5.94) | (1.40) | (0.19) | (2.88) | (1.85) | (1.63) | (0.24) | | |
| **Panel D: Asset Pricing Test of 20 Rating Momentum Spillover Portfolios (K = 2)** | | | | | | | | | | |
| *OLS regressions:* | | | | | | | | | | |
| Amihud liquidity | –0.03 | 0.65 | | | | | | | 0.48 | 0.14 |
| | (–0.33) | (3.40) | | | | | | | | |
| Amihud liquidity | –0.69 | 0.61 | 0.09 | 0.04 | 0.04 | –0.01 | 0.14 | –0.05 | 0.43 | 0.55 |
| | (–2.09) | (3.72) | (1.09) | (1.01) | (0.26) | (–1.62) | (3.70) | (–2.19) | | |
| PS liquidity | 0.04 | 0.13 | | | | | | | 0.56 | 0.10 |
| | (0.42) | (4.37) | | | | | | | | |
| PS liquidity | –0.53 | 0.11 | 0.11 | 0.01 | –0.04 | –0.01 | 0.13 | –0.06 | 0.41 | 0.54 |
| | (–1.75) | (4.38) | (1.37) | (0.10) | (–0.27) | (–1.36) | (3.49) | (–2.64) | | |
| *WLS regressions:* | | | | | | | | | | |
| Amihud liquidity | –0.01 | 0.52 | | | | | | | 0.32 | 0.13 |
| | (–0.12) | (2.70) | | | | | | | | |
| Amihud liquidity | –0.63 | 0.53 | 0.08 | 0.02 | –0.05 | –0.01 | 0.14 | –0.06 | 0.33 | 0.41 |
| | (–2.03) | (4.08) | (0.88) | (0.63) | (–0.28) | (–1.62) | (3.70) | (–2.50) | | |
| PS liquidity | 0.03 | 0.11 | | | | | | | 0.41 | 0.10 |
| | (0.35) | (3.33) | | | | | | | | |
| PS liquidity | –0.50 | 0.08 | 0.11 | 0.01 | –0.13 | –0.01 | 0.13 | –0.06 | 0.23 | 0.40 |
| | (–1.82) | (3.70) | (1.25) | (0.01) | (–0.79) | (–1.40) | (3.51) | (–2.89) | | |

$$r_{pt} - r_{ft} = \alpha_{S_t} + \beta_{1,S_t} MKT_t + \beta_{2,S_t} SMB_t + \beta_{3,S_t} HML_t + \beta_{4,S_t} DEF_t + \beta_{5,S_t} TERM_t + \beta_{6,S_t} L_t + \varepsilon_t \quad (6)$$

where $\varepsilon_t \sim N(0,\sigma^2_{S_t})$, $S_t = 1, 2$ represents bad and good states, respectively, and the intercept and coefficients are regime-dependent. $P(S_t = 1 | S_{t-1} = 1) = p$, $P(S_t = 2 | S_{t-1} = 2) = q$ are regime transition probability parameters. The regime-switching model postulates that the dynamics of portfolio returns are governed by a Markov chain with time-invariant transition probability. In this model, we treat states as inherently unobservable and extract information about them from the observed dynamics of portfolio returns.

In empirical estimation, the dependent variable is represented by a vector of excess returns for high- (P25) and low-momentum portfolios (P1) formed by the full sample and the high (P5) and low (P1) portfolios by each rating category with a total of 10 portfolios.[9] We use more conservative excess returns of momentum spillover portfolios at $K = 2$ in empirical estimation.[10] We jointly estimate the parameters of the factor model for the 10 high- and low-momentum portfolios where the regime indicators $S_t$ are identical for these portfolios in all $t$. The regime-switching model is estimated by maximum likelihood. Details of the estimation procedure are described in the appendix.

Exhibit 10 reports results of the regime-switching regression. For each liquidity measure used in the model, the first column reports parameter estimates for regime 1 (bad state) and the second column for regime 2 (good state). Panel A shows that estimates of transition probabilities are significant at the 5% level or higher, regardless of whether the liquidity factor is the Amihud or Pastor–Stambaugh measure. In all, 39 (46) months in the sample are classified as being associated with the bad state and 95 (106) months as the good state when using the Amihud (Pastor–Stambaugh) liquidity measure. The liquidity level is −0.05 (−0.02) in regime 1 versus 0.02 (0.01) in regime 2 when using the Pastor–Stambaugh (Amihud) measure as the liquidity factor. Results show that liquidity is lower in the unfavorable state.[11]

Panel B shows estimates of liquidity betas under the two regimes. Liquidity betas are higher in regime 1, indicating that momentum spillover portfolio returns are more sensitive to liquidity shocks in the unfavorable state. Using the Amihud (Pastor–Stambaugh) liquidity measure, liquidity betas for winner portfolios P25 are 0.63 (2.36) and 0.44 (1.91) in regimes 1 and 2, respectively. Correspondingly, liquidity betas are 0.23 (0.38) and 0.18 (0.32) for loser portfolios P1 in two separate regimes. All liquidity betas are significant at the 1% level. The liquidity beta spread between winner and loser portfolios widens in the unfavorable state. Liquidity beta spreads are 0.40 (1.98) in regime 1, compared with 0.26 (1.59) in regime 2 when using the Amihud (Pastor–Stambaugh) measure as the liquidity factor. All liquidity beta spreads are significant at the 1% level.

Similarly, liquidity betas are higher in regime 1 across rating categories. Moreover, the difference in the sensitivity to liquidity shocks between winner and loser portfolios increases with credit risk. For example, using the Amihud liquidity measure, the liquidity beta spread between winner (P5) and loser (P1) portfolios is 0.45 ($t = 6.58$) for speculative-grade bonds but only 0.01 ($t = 0.16$) for AAA/AA bonds in regime 1. Using the Pastor–Stambaugh liquidity measure, liquidity beta spreads are 2.18 and 0.02 with $t$ values of 21.06 and 0.15 for speculative-grade and AAA/AA bonds, respectively. Results for regime 2 show a similar pattern for the credit risk effect but with lower liquidity beta spreads for BBB and speculative-grade bonds.

Based on the results of the regime-switching model, we calculate profits of the momentum spillover strategy in each regime. Panel C of Exhibit 10 reports momentum spillover profits for the whole sample and different rating categories. Momentum spillover profits are significant at the 1% level in the favorable state but insignificant in the unfavorable state. Results are similar for both Amihud and Pastor–Stambaugh liquidity measures.

The profitability of momentum spillover strategies varies with credit risk. Results show an interesting contrast between the two regimes. In the favorable state (regime 2), momentum spillover profits increase as the rating decreases. The profit is 52 (55) bps per month for speculative-grade bonds but close to zero for AAA/AA bonds when using the Amihud (Pastor–Stambaugh) measure as the liquidity factor. On the other hand, in the unfavorable state (regime 1), the momentum spillover portfolio profit is insignificant for speculative-grade bonds. By contrast, AAA/AA momentum spillover portfolios have positive returns, which are significant at the 10% level when using the Pastor–Stambaugh measure as the liquidity factor.

## EXHIBIT 10

### Results of Regime-Switching Regression

This exhibit reports the results from the following regime-switching regression:

$$r_{pt} - r_{ft} = \alpha_{S_t} + \beta_{1,S_t} MKT_t + \beta_{2,S_t} SMB_t + \beta_{3,S_t} HML_t + \beta_{4,S_t} DEF_t + \beta_{5,S_t} TERM_t + \beta_{6,S_t} L_t + \varepsilon_t$$

where $\varepsilon_t \sim N(0, \sigma^2_{S_t})$, $S_t = 1$ and 2 indicate unfavorable and favorable regimes, respectively. The intercept and coefficients are regime-dependent and are estimated jointly for all portfolios. $P(S_t = 1 | S_{t-1} = 1) = p$, $P(S_t = 2 | S_{t-1} = 2) = q$ are regime transition probability parameters. The regime variables $S_t$ are the same across portfolios. The dependent variable includes the lowest and highest momentum portfolios formed by the full sample and by rating category. In all, there are 10 portfolios in the regression. Months classified as regime $S_t$ are those with a probability of more than 85% of being in that regime. The dependent variable is the portfolio return at $K = 2$ in excess of the one-month Treasury return. Panels A and B report estimates of transition probability and liquidity beta, and Panel C reports profits of momentum spillover strategies.

**Panel A: Transition Probabilities and Periods of High and Low Liquidity**

| | Amihud Measure | | PS Measure | |
|---|---|---|---|---|
| **Likelihood ratio test** | **172.99~$\chi^2$ (82)** | | **294.11~$\chi^2$ (82)** | |
| ***p*** | **0.42 (8.75)** | | **0.37 (8.62)** | |
| ***q*** | **0.76 (2.24)** | | **0.80 (4.05)** | |
| | **Regime 1** | **Regime 2** | **Regime 1** | **Regime 2** |
| Number of months | 39 | 95 | 46 | 106 |
| Mean liquidity level | −0.02 | 0.01 | −0.05 | 0.02 |

**Panel B: Liquidity Beta Estimates**

| | Amihud Measure | | PS Measure | |
|---|---|---|---|---|
| | **Regime 1** | **Regime 2** | **Regime 1** | **Regime 2** |
| Full Sample | | | | |
| 1 | 0.23 | 0.18 | 0.38 | 0.32 |
| | (4.77) | (4.32) | (5.21) | (4.43) |
| 25 | 0.63 | 0.44 | 2.36 | 1.91 |
| | (14.89) | (15.16) | (32.39) | (26.16) |
| 25-1 | 0.40 | 0.26 | 1.98 | 1.59 |
| | (5.18) | (6.22) | (19.15) | (15.36) |
| By Rating Category | | | | |
| AAA/AA | | | | |
| 1 | 0.12 | 0.06 | 0.30 | 0.15 |
| | (1.58) | (0.86) | (4.05) | (1.99) |
| 5 | 0.13 | 0.10 | 0.32 | 0.30 |
| | (1.78) | (0.91) | (4.25) | (4.15) |
| 5-1 | 0.01 | 0.04 | 0.02 | 0.15 |
| | (0.16) | (0.42) | (0.15) | (1.53) |
| A | | | | |
| 1 | 0.24 | 0.13 | 0.88 | 0.64 |
| | (4.25) | (1.58) | (12.08) | (8.77) |
| 5 | 0.39 | 0.29 | 1.77 | 1.50 |
| | (6.11) | (4.93) | (24.25) | (20.48) |
| 5-1 | 0.15 | 0.16 | 0.89 | 0.86 |
| | (2.12) | (3.61) | (8.61) | (8.28) |
| BBB | | | | |
| 1 | 0.15 | 0.11 | 0.46 | 0.40 |
| | (1.40) | (1.48) | (6.27) | (5.40) |
| 5 | 0.41 | 0.23 | 1.53 | 1.21 |
| | (5.31) | (3.21) | (20.94) | (16.53) |
| 5-1 | 0.26 | 0.12 | 1.07 | 0.81 |
| | (1.70) | (2.50) | (10.37) | (7.87) |
| Below BBB | | | | |
| 1 | 0.17 | 0.10 | 0.30 | 0.25 |
| | (4.75) | (3.88) | (4.09) | (3.39) |
| 5 | 0.62 | 0.42 | 2.48 | 2.00 |
| | (12.76) | (9.21) | (33.87) | (27.28) |
| 5-1 | 0.45 | 0.32 | 2.18 | 1.75 |
| | (6.58) | (6.12) | (21.06) | (16.90) |

## EXHIBIT 10 (*Continued*)

**Panel C: Profitability of Momentum Spillover Portfolios**

| | Amihud Measure | | | PS Measure | | |
|---|---|---|---|---|---|---|
| | Regime 1 | Regime 2 | Difference | Regime 1 | Regime 2 | Difference |
| Full Sample | | | | | | |
| 1 | 1.00 | 0.43 | –0.57 | 0.94 | 0.37 | –0.56 |
| 2 | 0.85 | 0.43 | –0.42 | 0.90 | 0.41 | –0.49 |
| 5 | 1.01 | 0.39 | –0.62 | 0.66 | 0.51 | –0.15 |
| 10 | 0.93 | 0.54 | –0.39 | 0.82 | 0.55 | –0.27 |
| 15 | 0.90 | 0.47 | –0.42 | 0.70 | 0.54 | –0.16 |
| 20 | 0.90 | 0.45 | –0.45 | 0.88 | 0.50 | –0.38 |
| 24 | 1.11 | 0.60 | –0.51 | 1.05 | 0.68 | –0.37 |
| 25 | 1.41 | 0.86 | –0.55 | 1.34 | 0.86 | –0.48 |
| 25-1 | 0.41 | 0.43 | 0.02 | 0.40 | 0.49 | 0.09 |
| | (0.90) | (2.64) | (0.06) | (1.05) | (3.01) | (0.25) |
| AAA/AA | | | | | | |
| 1 | 0.71 | 0.43 | –0.28 | 0.39 | 0.49 | 0.10 |
| 5 | 0.99 | 0.44 | –0.55 | 0.65 | 0.49 | –0.16 |
| 5-1 | 0.28 | 0.01 | –0.27 | 0.27 | 0.01 | –0.26 |
| | (1.59) | (0.18) | (–1.87) | (1.72) | (0.07) | (–1.93) |
| A | | | | | | |
| 1 | 0.89 | 0.44 | –0.45 | 0.77 | 0.48 | –0.29 |
| 5 | 0.86 | 0.60 | –0.26 | 0.88 | 0.62 | –0.26 |
| 5-1 | –0.04 | 0.17 | 0.20 | 0.11 | 0.14 | 0.03 |
| | (–0.10) | (2.03) | (0.84) | (0.47) | (1.59) | (0.13) |
| BBB | | | | | | |
| 1 | 0.95 | 0.38 | –0.57 | 0.76 | 0.37 | –0.39 |
| 5 | 1.05 | 0.54 | –0.51 | 0.89 | 0.59 | –0.30 |
| 5-1 | 0.10 | 0.17 | 0.07 | 0.13 | 0.22 | 0.09 |
| | (0.67) | (4.28) | (0.54) | (1.35) | (3.71) | (0.77) |
| Below BBB | | | | | | |
| 1 | 0.92 | 0.38 | –0.54 | 1.05 | 0.34 | –0.71 |
| 5 | 1.25 | 0.90 | –0.35 | 1.40 | 0.90 | –0.50 |
| 5-1 | 0.33 | 0.52 | 0.19 | 0.35 | 0.55 | 0.21 |
| | (1.19) | (4.10) | (0.72) | (1.62) | (3.98) | (0.81) |

The analysis above shows that the profitability of the momentum spillover strategy depends on states of nature. In the unfavorable regime, the momentum spillover strategy is profitable only for high-quality bonds (AAA/AA). This finding may be linked to the flight-to-quality phenomenon. To explore this possibility, we further examine the risk and returns of momentum spillover portfolios during the turbulent period.

### Momentum Spillover in the Liquidity Dry-Up Periods

To directly link profits of momentum spillover strategies to market liquidity conditions, we analyze portfolio returns in illiquid times of our sample period. The illiquid period is set to include the recent subprime crisis period (July 2007 to June 2009) and the months with the lowest 20% of the Amihud or Pastor–Stambaugh liquidity index in the whole sample. The period for the subprime crisis is consistent with the definition used by Dick-Nielsen et al. [2012].

Exhibit 11 reports the results. Panel A shows that profits of momentum spillover portfolios at $K = 2$ are insignificantly different from zero when market liquidity is low. This result holds for both the Amihud and Pastor–Stambaugh liquidity measures. When we further divide the whole sample into rating categories, an interesting pattern emerges. The profit of the momentum strategy is positive for AAA/AA bonds, but it is insignificantly different from zero for other bonds. For example, the profit is 27 bps per month for AAA/AA bonds when using the Amihud measure as the liquidity factor and 24 bps per month when using the Pastor–Stambaugh measure, both of which are significant at the 10% level. This result can

## Exhibit 11

### Momentum Spillover in Illiquid Market Periods

This exhibit reports the performance of momentum spillover portfolios in times of illiquidity. Returns or profits of 10-1 portfolios for the whole sample and 5-1 portfolios by rating are for the second month after portfolio formation ($K = 2$). The illiquidity period includes the recent financial crisis period (from July 2007 to June 2009) and the months with the lowest 20% liquidity in the whole sample based on the Amihud or Pastor–Stambaugh (PS) measure. The liquid period used in Panels A, B, and C is the whole sample period excluding the lowest 20% liquidity months and the crisis period.

Panel A reports returns of momentum spillover portfolios, and Panel B reports liquidity betas of portfolios in the illiquid period. Panel C reports differences in momentum spillover portfolio profits between the illiquid and liquid periods. Panel D reports average and aggregate values of trading volume and number of trades, as well as number of bonds traded per month for the crisis and normal periods. The crisis period is from July 2007 to June 2009. The normal period includes the subperiods from October 2004 to June 2007 and from July 2009 to September 2009.

**Panel A: Profitability of Momentum Spillover Portfolios**

| | Illiquidity Period–Amihud | | | Illiquidity Period–PS | | |
|---|---|---|---|---|---|---|
| **Portfolio** | **Obs.** | **Mean** | ***t*-value** | **Obs.** | **Mean** | ***t*-value** |
| 10-1 | 52 | 0.03 | 0.17 | 54 | 0.19 | 0.97 |
| AAA/AA | 52 | 0.27 | 1.86 | 54 | 0.24 | 1.82 |
| A | 52 | 0.04 | –0.17 | 54 | 0.02 | 0.11 |
| BBB | 52 | 0.08 | 0.70 | 54 | 0.13 | 1.25 |
| Below BBB | 52 | 0.32 | 1.45 | 54 | 0.30 | 1.49 |

**Panel B: Liquidity Beta**

| | Illiquidity Period–Amihud | | | | Illiquidity Period–PS | | | |
|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **Amihud** | ***t*-value** | **PS** | ***t*-value** | **Amihud** | ***t*-value** | **PS** | ***t*-value** |
| 10-1 | 0.36 | 1.55 | 1.78 | 1.71 | 0.52 | 2.13 | 1.25 | 1.17 |
| AAA/AA | 0.00 | 0.03 | –0.25 | –0.35 | –0.04 | –0.26 | 0.08 | 0.12 |
| A | 0.05 | 0.26 | 1.71 | 1.70 | 0.15 | 0.78 | 0.70 | 0.64 |
| BBB | 0.34 | 1.98 | 1.30 | 1.59 | 0.33 | 1.80 | 1.00 | 1.21 |
| Below BBB | 0.49 | 1.86 | 2.14 | 1.68 | 0.78 | 3.04 | 1.81 | 1.49 |

**Panel C: Return Differences between the Illiquid and Liquid Periods**

| | Illiquidity Period–Amihud | | Illiquidity Period–PS | |
|---|---|---|---|---|
| **Portfolio** | **Return Difference** | ***t*-value** | **Return Difference** | ***t*-value** |
| 10-1 | –0.44 | –2.40 | –0.23 | –1.26 |
| AAA/AA | 0.26 | 2.19 | 0.23 | 1.94 |
| A | –0.25 | –1.30 | –0.17 | –0.89 |
| BBB | –0.15 | –1.52 | –0.07 | –0.75 |
| Below BBB | –0.22 | –0.98 | –0.26 | –1.15 |

**Panel D: Trading of Corporate Bond Markets in the Financial Crisis and Normal Periods**

| **Rating** | **Period** | **Mean Volume (mln)** | **Mean Number of Trades** | **Aggregate Volume (bln)** | **Aggregate Number of Trades (thd)** | **Traded Bonds (thd)** |
|---|---|---|---|---|---|---|
| AAA/AA | Normal | 9.23 | 37.90 | 18.15 | 74.29 | 2.04 |
| | Crisis | 10.62 | 57.48 | 20.68 | 109.99 | 2.10 |
| A | Normal | 9.62 | 31.98 | 33.30 | 110.51 | 3.51 |
| | Crisis | 12.88 | 57.02 | 36.49 | 161.75 | 2.83 |
| BBB | Normal | 18.35 | 36.10 | 31.39 | 64.80 | 1.72 |
| | Crisis | 13.76 | 49.20 | 26.19 | 95.29 | 1.89 |
| Below BBB | Normal | 9.10 | 43.80 | 12.24 | 58.87 | 1.38 |
| | Crisis | 7.78 | 38.59 | 7.92 | 39.60 | 1.04 |

be attributed to the flight-to-quality phenomenon. When market liquidity dries up, investors become less willing to hold riskier bonds relative to high-quality bonds, which are more liquid. As there is more demand for high-quality bonds, prices of AAA/AA bonds are higher, leading to a profit for the momentum spillover strategy.

Panel B reports liquidity betas for portfolios with different ratings in times of low liquidity. The liquidity beta of AAA/AA bonds is close to zero, whereas those of BBB and junk bonds remain significantly positive. This pattern persists regardless of whether we use the Amihud or Pastor–Stambaugh measure. Results indicate that when market liquidity is low, returns of lower-grade bonds are more sensitive to liquidity shocks, possibly because investors are more worried about the future liquidity of these bonds. On the contrary, returns of high-quality AAA/AA bonds are not sensitive to aggregate liquidity shocks.

Panel C reports the differences in profits of momentum spillover portfolios between the illiquid and liquid periods.[12] The liquid period is the whole sample period excluding the lowest 20% liquidity months and the crisis period. A positive number indicates higher profits in the illiquid period. Results show that the momentum spillover profit for AAA/AA bonds is significantly higher in the illiquid period. By contrast, the profit is lower in the illiquid period for other bonds. These results are consistent with the estimates of the regime-switching regression.

The standard measure of liquidity in the literature is trading volume and frequency. We further examine the trading activity for bonds in each rating category. To provide a sharper contrast, we focus on only the trading activity surrounding the subprime crisis period, instead of the whole illiquid period.

Panel D reports average and aggregate volume and number of trades and number of bonds traded per month for the normal and crisis periods. For each month, we calculate the average and total volumes and then take the average for these two volume series. The crisis period is again from July 2007 to June 2009. The normal period covers the periods from October 2004 to June 2007 and from July to September 2009. We choose October 2004 as the starting month for the normal period to avoid a big jump in volume from the prior months due to the large expansion in the coverage of bonds in TRACE at the beginning of that month. This arrangement provides a more effective control period.

Results in Panel D confirm that liquidity improves for high-grade bonds but deteriorates for low-grade bonds during the crisis. Trading volume increases during the crisis period for high-grade bonds but decreases for low-grade bonds. The speculative-grade bonds experience the worst deterioration in liquidity. The aggregate volume and number of trades decrease by 35% and 33%, respectively, and the number of bonds traded per month drops by 25% for these bonds. The average and total volumes for BBB bonds also decline by 25% and 17% respectively. Thus, during the turbulent period, the volume of riskier bonds dries up faster. Results show that the liquidity risk of low-grade bonds manifests itself in trading activities. The liquidity risk of low-grade bonds is higher because the liquidity of these bonds is more likely to decline in times of stress, thus precipitating a substantial loss in value.

## CONCLUSIONS

Pronounced momentum returns across different markets pose a serious challenge to standard finance theory. Despite the extensive literature, this issue is surprisingly underexplored for the corporate bond market. Various explanations have been proposed to explain the momentum anomaly. However, the literature has not settled on a generally accepted explanation for momentum returns. Recently, liquidity risk has been proposed as a plausible explanation for momentum returns (see Pastor and Stambaugh [2003]; Sadka [2006]). Using a comprehensive transaction dataset, this article expands the current literature by documenting the first evidence on the role of liquidity risk in the momentum spillover anomaly of corporate bonds.

We find a significant equity momentum spillover effect from equities to speculative-grade bonds, and this effect is much stronger than that documented in the literature for investment-grade bonds. More importantly, we find a close relation between liquidity risk and the equity momentum spillover. There is strong evidence that liquidity risk is priced in the momentum spillover portfolio returns. The liquidity risk premium accounts for a larger proportion of the momentum spillover return for lower-grade bonds. A significant portion of equity momentum spillover returns can be construed as compensation for investors bearing liquidity risk. This finding is robust to controls for effects of behavioral factors and bond characteristics. Results show that the same equity-based liquidity risk factors that explain the stock momentum effect also explain the equity momentum spillover effect in the corporate bond market.

The analysis of momentum returns during the illiquid periods provides further insight into the role of the liquidity risk factor. The liquidity of low-grade bonds dries up faster during the financial crisis period. Returns of these bonds have much higher sensitivities (betas) to aggregate liquidity shocks. The price of low-grade bonds drops substantially during the crisis period because of the flight-to-quality phenomenon. In anticipation of costly liquidation in a low-liquidity environment, investors require higher expected returns for low-grade bonds. This explains why momentum spillover portfolios consisting of speculative-grade bonds have both high returns and high liquidity betas. Our empirical evidence shows that liquidity plays a significant role in the momentum spillover of corporate bonds and that the liquidity risk of the high momentum spillover portfolio manifests itself in the trading activities of the underlying bonds.

## APPENDIX

### Estimation of the Regime-Switching Model

This appendix illustrates how we estimate the regime-switching model. The regime-switching model of portfolio returns is

$$\begin{aligned} r_{pt} - r_{ft} &= \alpha_{S_t} + \beta_{1,S_t} MKT_t + \beta_{2,S_t} SMB_t + \beta_{3,S_t} HML_t + \beta_{4,S_t} DEF_t \\ &\quad + \beta_{5,S_t} TERM_t + \beta_{6,S_t} L_t + \varepsilon_t \end{aligned}$$

where $\varepsilon_t \sim N(0, \sigma^2_{S_t})$ and $S_t = 1, 2$ for all. $t$ is the unobserved regime indicator for regimes 1 and 2, respectively. The regime-switching model assumes that the dynamics of $S_t$ are described by a Markov chain with time-invariant transition probability:

$$P(S_t = 1 \mid S_{t-1} = 1) = p$$
$$P(S_t = 2 \mid S_{t-1} = 2) = q$$

where the sum of transition probabilities is equal to one.

We jointly estimate parameters of the model for high- and low-momentum spillover portfolios by maximum likelihood. Let $I_t = \{r_1, \ldots, r_t\}$ where $r_t$ is the vector of bond excess returns at time $t$, $t = 1, 2, \ldots, T$. Also, let $x_t$ be the information set of factors, and $\theta$ be the vector of unknown parameters. In our model, $r_t$ contains returns of 10 portfolios, which include portfolios 1 and 25 formed from the full sample and portfolios 1 and 5 formed for each rating category (AAA/AA, A, BBB, and below BBB), and $x_t$ includes observations for the six factors. The conditional likelihood $f(r_t|x_t,I_{t-1};\theta)$ at time $t$ can be calculated as the weighted average of conditional likelihood under two regimes:

$$\begin{aligned} &f(r_t \mid x_t, I_{t-1};\theta) \\ &= f(r_t, S_t = 1 \mid x_t, I_{t-1};\theta) + f(r_t, S_t = 2 \mid x_t, I_{t-1};\theta) \\ &= f(r_t \mid S_t = 1, x_t, I_{t-1};\theta) \times P(S_t = 1 \mid x_t, I_{t-1};\theta) \\ &\quad + f(r_t \mid S_t = 2, x_t, I_{t-1};\theta) \times P(S_t = 2 \mid x_t, I_{t-1};\theta) \\ &= \eta_{1t} \times P(S_t = 1 \mid x_t, I_{t-1};\theta) + \eta_{2t} \times P(S_t = 2 \mid x_t, I_{t-1};\theta) \end{aligned}$$

where

$$\eta_{1t} = \frac{1}{\sqrt{\det(2\pi\Omega_1)}} \exp\left( - \frac{E_{1t}'\Omega_1^{-1}E_{1t}}{2} \right)$$
$$\eta_{2t} = \frac{1}{\sqrt{\det(2\pi\Omega_2)}} \exp\left( - \frac{E_{2t}'\Omega_2^{-1}E_{2t}}{2} \right)$$

$E_{1t}$ and $E_{2t}$ are the time $t$ vectors of return residuals $\varepsilon_t$, and $\Omega_1$ and $\Omega_2$ are the variance-covariance matrix of return residuals with off-diagonal terms equal to zeros under regimes 1 and 2, respectively. Moreover,

$$\begin{aligned} &P(S_t = i \mid x_t, I_{t-1};\theta) \\ &= P(S_t = i, S_{t-1} = 1 \mid x_t, I_{t-1};\theta) + P(S_t = i, S_{t-1} = 2 \mid x_t, I_{t-1};\theta) \\ &= P(S_t = i \mid S_{t-1} = 1, x_t, I_{t-1};\theta) \times P(S_{t-1} = 1 \mid x_t, I_{t-1};\theta) \\ &\quad + P(S_t = i \mid S_{t-1} = 2, x_t, I_{t-1};\theta) \times P(S_{t-1} = 2 \mid x_t, I_{t-1};\theta) \\ &= \begin{cases} p \times P(S_{t-1} = 1 \mid x_t, I_{t-1};\theta) + (1-q) \times P(S_{t-1} = 2 \mid x_t, I_{t-1};\theta), & i = 1 \\ (1-p) \times P(S_{t-1} = 1 \mid x_t, I_{t-1};\theta) + q \times P(S_{t-1} = 2 \mid x_t, I_{t-1};\theta), & i = 2 \end{cases} \end{aligned}$$

and

$$\begin{aligned} &P(S_{t-1} = i \mid x_t, I_{t-1};\theta) \\ &= P(S_{t-1} = i \mid x_t, r_{t-1}, I_{t-2};\theta) \\ &= \frac{f(r_{t-1}, S_t = i \mid x_{t-1}, I_{t-2};\theta)}{f(r_{t-1} \mid x_{t-1}, I_{t-2};\theta)}, \; i = 1, 2 \end{aligned}$$

The initial value $P(S_0 = i|x_1,I_0;\theta)$ equals the unconditional regime probability, which is $(1-q)/(2-p-q)$ when $i = 1$ and $(1-p)/(2-p-q)$ when $i = 2$. From $P(S_0 = i|x_1,I_0;\theta)$, we first calculate $P(S_1 = i|x_1,I_0;\theta)$ and $f(r_1|I_0;\theta)$, and then recursively calculate $f(r_2|x_2,I_1;\theta), \ldots, f(r_T|x_T,I_{T-1};\theta)$. Parameters $\theta$ are chosen to maximize the log-likelihood $\sum_{t=1}^{T} \log f(r_t \mid x_t, I_{t-1};\theta)$, that is,

$$\hat{\theta} = \arg\max_{\theta} \sum_{t=1}^{T} \log f\left(r_t \mid x_t, I_{t-1}; \theta\right)$$

Let $P(S_t = i \mid x_t, I_t; \hat{\theta})$ denote the inference about the value of $S_t$ based on the data through time $t$ and estimated parameters $\hat{\theta}$. This inference measures the possibility that the $t$th observation was generated by regime $i$. Denote the conditional probability vector $\begin{bmatrix} P(S_t = 1 \mid x_t, I_t; \hat{\theta}) \\ P(S_t = 2 \mid x_t, I_t; \hat{\theta}) \end{bmatrix}$ by $\hat{\xi}_{t|t}$. Conditional probabilities can be calculated by iterations through the following relations:

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t|t-1} \circ \eta_t}{1'\left(\hat{\xi}_{t|t-1} \circ \eta_t\right)}$$

$$\hat{\xi}_{t+1|t} = H \cdot \hat{\xi}_{t|t}, \text{ and}$$

$$\hat{\xi}_{0|0} = \begin{bmatrix} (1-q)/(2-p-q) \\ (1-p)/(2-p-q) \end{bmatrix},$$

where $\hat{\xi}_{t|t-1} = \begin{bmatrix} P(S_t = 1 \mid x_t, I_{t-1}; \hat{\theta}) \\ P(S_t = 2 \mid x_t, I_{t-1}; \hat{\theta}) \end{bmatrix}$, $\eta_t = \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix}$

$H = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix}$, 1 is a 2x1 unit vector, and $\circ$ denotes element-by-element multiplication. In empirical estimation, we define a state as regime 1 if $P(S_t = 1 \mid x_t, I_t; \hat{\theta}) \geq 85\%$ and as regime 2 if $P(S_t = 2 \mid x_t, I_t; \hat{\theta}) \geq 85\%$.

To test whether the regime-switching effect is significant, we estimate the model without regime switching. Let the log-likelihood value of the regime-switching model be $L_{RS}$ and that of the model without regime switching be $L_{TR}$. The likelihood ratio test is used to determine whether the regime-switching effect is significant. The test statistic is $L = 2 \times (L_{RS} - L_{TR})$, which follows a chi-square distribution with a degree of freedom equal to the number of restricted parameters (82 in our model).

## ENDNOTES

[1]Momentum strategies involve high portfolio turnover and nontrivial trading costs (Moskowitz and Grinblatt [1999]; Grundy and Martin [2001]). Several studies have examined whether strategies used to exploit momentum anomalies can be profitable after accounting for transaction costs (Lesmond, Schill, and Zhou [2004]; Korajczyk and Sadka [2004]). Menkhoff et al. [2012] find that currency momentum returns are partially explained by transaction costs.

[2]They find that bond returns exhibit reversal instead. Khang and King [2004] report a similar finding.

[3]Gebhardt et al. [2005] study the spillover effect only for investment-grade bonds.

[4]Initially (Phase I), TRACE covered about 500 U.S. investment-grade corporate bonds with an original issue size of at least \$1 billion. On March 1, 2003 (Phase II), TRACE expanded its coverage of transactions to include bonds rated A and above with issue size of greater than \$100 million and 120 Baa bonds with issue size of less than \$1 billion. On October 1, 2004 (Phase III), the database was further expanded to cover all publicly traded corporate bonds.

[5]Datastream data are usually perceived to be of not as good quality as the other sources.

[6]See mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[7]We use six lags in the Newey–West procedure, which is found to be sufficient for the autocorrelation correction.

[8]Results for value-weighted portfolios are available on request.

[9]These include portfolios 1 and 25 formed from the full sample and portfolios 1 and 5 for each rating category (AAA/AA, A, BBB, and below BBB).

[10]The results based on excess returns at $K = 1$ are stronger. Thus, results at $K = 2$ provide a low bound.

[11]Months classified as state 1 or 2 are those with a probability of more than 85% of being in that state.

[12]Subtracting the return in Panel C from that in Panel A gives the return in the liquid period for each group of bonds.

## REFERENCES


Amihud, Y. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, 5 (2002), pp. 31-56.

Asness, C., T. Moskowitz, and L. Pedersen. "Value and Momentum Everywhere." *The Journal of Finance*, 68 (2013), pp. 929-985.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov. "Momentum and Credit Rating." *The Journal of Finance*, 62 (2007), pp. 2503-2520.

Bao, J., J. Pan, and J. Wang. "The Illiquidity of Corporate Bonds." *The Journal of Finance*, 66 (2011), pp. 911-946.

Bessembinder, H., K. Kahle, W. Maxwell, and D. Xu. "Measuring Abnormal Bond Performance." *Review of Financial Studies*, 22 (2009), pp. 4219-4258.

Cai, N., J. Helwege, and A. Warga. "Underwriting in the Corporate Bond Market." *Review of Financial Studies*, 20 (2007), pp. 2021-2046.

Campbell, J.Y., and G.B. Taksler. "Equity Volatility and Corporate Bond Yields." *The Journal of Finance*, 58 (2003), pp. 2321-2349.

Chabot, B.R., E. Ghysels, and R. Jagannathan. "Momentum Cycles and Limits to Arbitrage: Evidence from Victorian England and Post-Depression US Stock Markets." NBER Working Paper W15591, 2009.

Chan, K.C., N. Jegadeesh, and J. Lakonishok. "Momentum Strategies." *The Journal of Finance*, 51 (1996), pp. 1681-1713.

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

Chui, A., S. Titman, and K.C. Wei. "Individualism and Momentum around the World." *The Journal of Finance*, 65 (2010), pp. 361-392.

Dick-Nielsen, J., P. Feldhutter, and D. Lando. "Corporate Bond Liquidity before and after the Onset of the Subprime Crisis." *Journal of Financial Economics*, 103 (2012), pp. 471-492.

Elton, J.E., M.J. Gruber, D. Agrawal, and C. Mann. "Explaining the Rate Spread on Corporate Bonds." *The Journal of Finance*, 56 (2001), pp. 247-277.

Fama, E.F., and K.R. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance*, 47 (1992), pp. 427-465.

——. "Common Risk Factors in the Returns of Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), pp. 3-56.

——. "Size, Value, and Momentum in International Stock Returns." *Journal of Financial Economics*, 105 (2012), pp. 457-472.

Fama, E.F., and J. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 71 (1973), pp. 680-692.

Friewald, N., R. Jankowitsch, and M. Subrahmanyam. "Illiquidity or Credit Deterioration: A Study of Liquidity in the US Corporate Bond Market during Financial Crises." *Journal of Financial Economics*, 105 (2012), pp. 18-36.

Gebhardt, W.R., S. Hvidkjaer, and B. Swaminathan. "Stock and Bond Market Interaction: Does Momentum Spill Over?" *Journal of Financial Economics*, 75 (2005), pp. 651-690.

Gervais, S., and T. Odean. "Learning to Be Overconfident." *Review of Financial Studies*, 14 (2001), pp. 1-27.

Glaser, M., and M. Weber. "Which Past Returns Affect Trading Volume?" *Journal of Financial Markets*, 12 (2009), pp. 1-31.

Gorton, G.B., F. Hayashi, and K.G. Rouwenhorst. "The Fundamentals of Commodity Futures Returns." Working paper, Yale University, 2008.

Griffin, J.M., X. Ji, and J.S. Martin. "Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole." *The Journal of Finance*, 58 (2003), pp. 2515-2547.

Grundy, B.D., and J.S. Martin. "Understanding the Nature of the Risks and the Sources of the Rewards to Momentum Investing." *Review of Financial Studies*, 14 (2001), pp. 29-78.

Hong, H., and J. Stein. "A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets." *The Journal of Finance*, 54 (1999), pp. 2143-2184.

Hotchkiss, E.S., and T. Ronen. "The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis." *Review of Financial Studies*, 15 (2002), pp. 1325-1354.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance*, 48 (1993), pp. 65-91.

——. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *The Journal of Finance*, 56 (2001), pp. 699-720.

Kandel, S., and R.F. Stambaugh. "Portfolio Inefficiency and the Cross-Section of Expected Returns." *The Journal of Finance*, 50 (1995), pp. 157-184.

Khang, K., and T.D. King. "Return Reversals in the Bond Market: Evidence and Causes." *Journal of Banking and Finance*, 28 (2004), pp. 569-593.

Kho, B. "Time-Varying Risk Premia, Volatility, and Technical Reading Profits: Evidence from Foreign Currency Futures Markets." *Journal of Financial Economics*, 41 (1996), pp. 249-290.

Korajczyk, R.A., and R. Sadka. "Are Momentum Profits Robust to Trading Costs?" *The Journal of Finance*, 59 (2004), pp. 1039-1082.

Korajczyk, R.A., and R. Sadka. "Pricing the Commonality across Alternative Measures of Liquidity." *Journal of Financial Economics*, 87 (2008), pp. 45-72.

Krishnan, C.N.V., P.H. Ritchken, and J.B. Thomson. "Monitoring and Controlling Bank Risk: Does Risky Debt Help?" *The Journal of Finance*, 60 (2005), pp. 343-378.

Kwan, S.H. "Firm-Specific Information and the Correlation between Individual Stocks and Bonds." *Journal of Financial Economics*, 40 (1996), pp. 63-80.

LeBaron, B. "Technical Trading Rule Profitability and Foreign Exchange Intervention." *Journal of International Economics*, 49 (1999), pp. 125-143.

Lesmond, D.A., M.J. Schill, and C. Zhou. "The Illusory Nature of Momentum Profits." *Journal of Financial Economics*, 71 (2004), pp. 349-380.

Lewellen, J., S. Nagel, and J. Shanken. "A Skeptical Appraisal of Asset Pricing Tests." *Journal of Financial Economics*, 96 (2010), pp. 175-194.

Lin, H., J. Wang, and C. Wu. "Liquidity Risk and Expected Corporate Bond Returns." *Journal of Financial Economics*, 99 (2011), pp. 628-650.

Litzenberger, R.H., and K. Ramaswamy. "The Effect of Personal Taxes and Dividends on Capital Asset Prices: Theory and Empirical Evidence." *Journal of Financial Economics*, 7 (1979), pp. 163-195.

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

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf. "Currency Momentum Strategies." *Journal of Financial Economics*, 106 (2012), pp. 660-684.

Moskowitz, T.J., and M. Grinblatt. "Do Industries Explain Momentum?" *The Journal of Finance*, 54 (1999), pp. 1249-1290.

Næs, R., J. Skjeltorp, and B. Ødegaard. "Stock Market Liquidity and the Business Cycle." *The Journal of Finance*, 66 (2011), pp. 139-176.

Newey, W., and K. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), pp. 703-708.

Odean, T. "Volume, Volatility, Price, and Profit When All Traders Are Above Average." *The Journal of Finance*, 53 (1998), pp. 1887-1934.

Okunev, J., and D. White. "Do Momentum-Based Strategies Still Work in Foreign Currency Markets?" *Journal of Financial and Quantitative Analysis*, 38 (2003), pp. 425-447.

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

Rouwenhorst, K.G. "International Momentum Strategies." *The Journal of Finance*, 53 (1998), pp. 267-284.

Sadka, R. "Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk." *Journal of Financial Economics*, 80 (2006), pp. 309-349.

——. "Liquidity Risk and the Cross-Section of Hedge-Fund Returns." *Journal of Financial Economics*, 98 (2010), pp. 54-71.

Sarig, O., and A. Warga. "Bond Price Data and Bond Market Liquidity." *Journal of Financial and Quantitative Analysis*, 24 (1989), pp. 367-378.

Scheinkman, J., and W. Xiong. "Overconfidence and Speculative Bubbles." *Journal of Political Economy*, 111 (2003), pp. 1183-1219.

Shanken, J. "On the Estimation of Beta-Pricing Models." *Review of Financial Studies*, 5 (1992), pp. 1-33.

Shanken, J., and G. Zhou. "Estimating and Testing Beta Pricing Models: Alternative Methods and Their Performance in Simulations." *Journal of Financial Economics*, 84 (2007), pp. 40-86.

Statman, M., S. Thorley, and K. Vorkink. "Investor Overconfidence and Trading Volume." *Review of Financial Studies*, 19 (2006), pp. 1531-1565.

Teo, M. "The Liquidity Risk of Liquid Hedge Funds." *Journal of Financial Economics*, 100 (2011), pp. 24-44.

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## Liquidity Risk and Momentum Spillover from Stocks to Bonds 5

Hai Lin, Junbo Wang, and Chunchi Wu

This article investigates the role of liquidity risk in the momentum spillover from stocks to bonds by using a large data sample. The evidence strongly suggests that liquidity risk is an important determinant of momentum spillover returns. This finding is robust to controls for effects of trading liquidity, credit risk, behavioral factors, and bond characteristics. On average, liquidity risk explains about 40% of momentum spillover profits for investment-grade bonds and 55% for speculative-grade bonds over the 16-year sample period. A significant portion of momentum spillover returns can be viewed as compensation for investors' exposure to liquidity risk when engaging in trading this anomaly.

## Quantifying and Explaining the New-Issue Premium in the Post-Glass–Steagall Corporate Bond Market 43

Robert S. Goldberg and Ehud I. Ronn

The authors document and rationalize the premium paid by bond issuers in the corporate bond markets. Changes in the bond market over the past 30 years have shifted the new-issue pricing risk from investors to banks and back to investors, with large institutional investors acting as a de facto adjunct underwriting group, and this process has required both capital commitment as well as a commitment to taking on unsystematic risk for which investors require compensation. The authors use the superior data prevalent in trades under the TRACE system to compute the new-issue premium (NIP) and relate the magnitude of that premium to predetermined economic variables: the level of the corporate bond spread; the future volatility of swap spreads; the prevailing value of unsystematic risk in the bond markets; the spread of the issuer to the Treasury market at time of issuance; and the tenor of the new bond issue. They then present a model for the required NIP based on compensation for information uncertainty and the bearing of unsystematic risk. In so doing, they also address the issues of oligopolistic pricing and wealth transfer that occur at time of issuance.

## Structural Credit Loss Distributions under Non-Normality 56

Enrique Batiz-Zuk, George Christodoulakis, and Ser-Huang Poon

In the context of Merton [1974] and Vasicek [1987, 2002] Gaussian single-factor credit risk models, the authors examine the impact of neglected non-normality of the underlying asset return process on the shape of the derived credit loss distribution and the resulting Basel capital requirements. They relax the Gaussian assumption and specify skew-normal and skew-student $t$ densities to model the underlying asset return process, thus generalizing the credit loss distribution, and develop a maximum-likelihood estimator for the structural parameters. They apply their approach to aggregate charge-off rates published by the Federal Reserve Board for 10 U.S. sectors.

The authors show that the non-gaussian modeling of the common factor provides a better characterization of data than its Gaussian counterpart and that it has a significant impact on the capital requirements, depending on the sign and magnitude of the skew-related coefficient. On the other hand, the non-gaussian modeling of the idiosyncratic factor does not provide a significantly better characterization than the Gaussian base case. The latter could stem from the fact that the sector portfolios are large, so the idiosyncratic component has been diversified away.