Stock Market Liquidity and the Long-Run Stock Performance of Debt Issuers

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Previous studies document that the stock returns of bond issuing firms significantly underperform matched peers over the three to five years following issuance. We revisit this phenomenon and show that the underperformance is the result of an omitted return factor (a "bad model problem"). Debt issuers have significantly higher stock market liquidity than size and book-to-market matched counterparts, and differences in liquidity are largest for the worst performing groups of issuers. When we additionally match on liquidity or when we include a liquidity factor in the model for expected returns, the evidence of underperformance disappears.

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Previous studies document that the stock returns bond issuers significantly underperform matched peers over the three to five years following issuance. We revisit this phenomenon and show that the underperformance is the result of an omitted return factor (a "bad model problem"). Debt issuers have significantly higher stock market liquidity than size and book-to-market matched counterparts, and differences in liquidity are largest for the worst performing groups of issuers. When we additionally match on liquidity or when we include a liquidity factor in the model for expected returns, the evidence of underperformance disappears.

There is substantial controversy about whether firms can successfully time their corporate decisions to exploit information advantages they may have over security market participants. Much of this debate has centered on the long-run stock performance of security issuing firms, especially those issuing equity. Ritter (1991), Loughran and Ritter (1995), and Spiess and Affleck-Graves (1995) all find statistically significant long-run stock return underperformance following equity issues.[1] These findings, though, have been challenged on a number of grounds. For instance, Mitchell and Stafford (2000) argue that because the multi-year abnormal returns of event firms are cross-correlated, the usual test statistics for abnormal performance are overstated. Schultz (2003) argues that researchers are likely to observe ex post (but not ex ante) abnormal performance in event time if the number of events is endogenous. Specifically, Schultz (2003) argues that if equity issues are more likely when market levels are high, then a researcher will find a disproportionately large number of events at market peaks which increases the ex post probability of observing underperformance even when ex ante returns are unpredictable. Eckbo, Masulis, and Norli (2000) argue that issuing equity reduces the firm's leverage and risk characteristics relative to matched firms, making sample firms' required returns lower than their matched firm counterparts. Eckbo and Norli (2005) argue that equity issuing firms are more liquid than non-issuing matched firms, and thus command lower required returns.

We take up the question of the long-run stock performance of debt and convertible debt issuers. Spiess and Affleck-Graves (1999) show that debt and convertible debt issuers significantly underperform benchmark firms over the five years following issuance, and Lee and

[1] These are but a few papers that document this basic result. Brav and Gompers (1997), Brav, Geczy and Gompers (2000), and Gompers and Lerner (2003) find mixed, weak, or no evidence that individual equity issues underperform the market on a risk-adjusted basis. Butler, Grullon, and Weston (2005a) show that aggregate equity issues have no out-of-sample predictive power for future market returns.

Loughran (1998) document similar underperformance for convertible issuers.[2] Many of the important criticisms of the equity issuer underperformance studies do not apply to studies of debt issuers. Spiess and Affleck-Graves (1999) use calendar time regressions, thereby mitigating concerns like those raised by Mitchell and Stafford (2000) and Schultz (2003). The critique of Eckbo, Masulis, and Norli (2000) suggests that, if anything, the underperformance of debt issuers might be underestimated. In this paper we confront the data with the hypothesis that the apparent long-run underperformance of debt and convertible debt issuers is driven by a "bad model problem" that results from an omitted factor that affects returns: stock market liquidity.

A large number of recent papers show that liquidity affects cross-sectional variation of stock returns or the firm's cost of raising external capital.[3] Barber and Lyon (1997) argue that "…as future research in financial economics discovers additional variables that explain the cross-sectional variation in common stock returns, it will also be important to consider these additional variables when matching sample firms to control firms (pp. 370-1)." It is in this spirit that we examine whether debt issuers and convertible debt issuers have similar liquidity characteristics to benchmark firms that are matched by size and book-to-market and find that they do not.

Firms choose whether to issue public debt, and this self-selection creates differences in stock market liquidity between firms that choose to issue public debt and those that do not. We show this directly by modeling the debt issuance choice as a function of stock market liquidity

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[2] Note that the puzzle presented by these papers is that debt issuing firms' *equity* underperforms, not whether debt issuance decisions are related to future bond returns. Butler, Grullon, and Weston (2006) and Barry, et al. (2005) show that managers are unable to successfully time their debt issues in anticipation of future changes in interest rates.

[3] Closely related to our premise, Eckbo and Norli (2005) show that liquidity plays an important role in explaining the apparent post-issue underperformance of equity issuers. Other papers that document the importance of liquidity for valuation include Amihud and Mendelson (1986, 1989), Brennan and Subrahmanyam (1996), Amihud, Mendelson, and Lauterbach (1997), Eleswarapu (1997), Brennan, Chordia, and Subrahmanyam (1998), and Easley, Hvidkjaer, and O'Hara (2002), all of which provide evidence that firm specific liquidity affects the cross section of security returns; Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Fujimoto and Watanabe (2006), and Sadka (2005) show that variation in market liquidity affects security returns; Butler, Grullon, and Weston (2005b) shows that liquidity reduces the direct costs of issuing seasoned equity.

and a battery of control variables. We find that liquidity is a significant determinant of issuing public debt, which is consistent with Odders-White and Ready (2006), who show that firms with liquid stock have better credit quality than illiquid counterparts (this bears out in our sample as well), and Denis and Mihov (2003) who show that firms with better credit quality are more likely to issue public debt (and thus be candidates for our sample) than to issue private debt. Additionally, liquidity may affect the direct costs, and hence the likelihood, of security issuance. Butler, Grullon, and Weston (2005b) show that stock liquidity affects the direct cost of issuing equity. We replicate their analysis for our bond issuers, and find that stock liquidity also significantly affects the direct cost of issuing debt. Further, not only does liquidity affect these direct issuance costs, but the costs are most sensitive to illiquidity in exactly the groups that have the worst liquidity mismatches. In short, a particular firm is more likely to appear in a sample of public debt issuers precisely because it has better liquidity.

Consistent with our probit model, our sample firms have statistically significantly higher post-issue stock market liquidity than benchmark firms matched on exchange, size, and book-to-market. Given the numerous papers (see references above) that find that various measures of liquidity are priced in the cross-section of stock returns, we hypothesize that this difference in liquidity may reduce the required returns for sample firms relative to their benchmarks during the post-issue period.

We investigate this hypothesis as follows. First, we replicate the Spiess and Affleck-Graves (1999) study, extending their sample ten years through 1999 and find results very similar to theirs. Specifically, in event time tests, debt issuers underperform size and book-to-market matched firms by a statistically significant and economically large -24% over the five years following issuance. Nasdaq-listed issuers show especially bad mean abnormal performance at -

79% over five years (median = -38%). Our calendar time tests also show underperformance; tests using equally weighted portfolios still show underperformance of a statistically significant -21 basis points per month, or about -12% over five years (tests using value-weighting show no significant underperformance).

After replicating the Spiess and Affleck-Graves (1999) tests, we turn our attention to examining whether matching benchmark firms on size and book-to-market adequately captures differences in liquidity. We find that, on average, there are statistically significant liquidity differences at the time of the debt or convertible debt offerings, with sample firms being more liquid than benchmark firms. Furthermore, the same categories that have the worst underperformance are the ones that are most mismatched based on liquidity. That is, the worst performing firms have systematically and significantly higher liquidity than their benchmarks matched on size and book-to-market alone.

We next examine whether these differences in liquidity are at the root of the relative underperformance of the stock returns of debt and convertible debt issuers. For the event time tests, we match on pre-issue liquidity in addition to size and book-to-market.[4] For our calendar time regressions, we include a liquidity factor in the pricing model.

Controlling for liquidity drastically changes the results, especially for the event time tests. No longer is underperformance of debt issuers large or routinely significant. Indeed, the groups that have the worst performance relative to benchmark firms matched only on size and book-to-market now have abnormal performance that is reliably indistinguishable from zero when matched on liquidity as well as size and book-to-market.

[4] Differences in liquidity during the *post-issue* period may be responsible for apparent underperformance of sample firms. To construct conservative tests, however, we match on *pre-issue* liquidity to ensure that we are not using hindsight in constructing our matched sample.

We then add a liquidity factor to our calendar time tests. We construct our liquidity factor in two different ways—using the Amihud (2002) measure of illiquidity, and using average share turnover. For an equal-weighted portfolio of issuers, when we augment the Fama-French model with a liquidity factor, abnormal performance is no longer significant (the value weighted portfolio produces insignificant intercepts even using just the simpler three factor model).

The bottom line from our analysis is that debt and convertible debt issuers appear to have systematically better liquidity than benchmark firms, the liquidity differences are largest where underperformance appears to be the most severe, and controlling for liquidity by having an additional matching criterion eliminates the underperformance. In short, liquidity mismatches seem to be driving the apparent underperformance of debt issuers.

I. Data

We start with a list of new debt offerings from the Securities Data Company New Issues database during the period 1975-1999. We follow Spiess and Affleck-Graves (1999) in imposing the following requirements: (1) the company is listed on the Center for Research in Securities Prices (CRSP) and Compustat database at the time of the issuance; (2) the company is listed in NYSE, AMEX, or Nasdaq; (3) the company is not a regulated utility (SIC 4900-4949) or a financial institution (SIC 6000-6999); (4) traded shares are ordinary common shares; ADRs, SBIs, REITs, and closed-end funds are omitted; and (5) the issue is not a unit offering and does not include warrants. Our sample extends the Spiess and Affleck-Graves sample an additional ten years through 1999. Applying these criteria results in a sample of 4293 offerings, of which 3661 are straight debt offerings and 632 are convertible debt offerings. Because all of our test statistics are based on the assumption that the observations are independent, we restrict our analysis to the subset of observations for which there is no overlap of the five-year post-offering windows for repeat issues. We note, though, that our conclusions are not sensitive to the inclusion or exclusion of observations that occur inside the five year window we impose. That is, we start with the first offering in the sample period for a particular firm and exclude from the sample any offerings the same firm makes within the following five years.[5] For each independent observation, we require a matched firm based on size and book-to-market and a matched firm based on size, book-to-market, and liquidity. The final sample consists of 1102 issues, of which 799 are straight debt offerings and 303 are convertible debt offerings. In Table I, we present the distribution by year for our sample of non-overlapping debt and convertible debt offerings.

(Insert Table I here)

Table II presents some distributional characteristics of our sample firms. Despite our sample selection criterion that eliminates issues within five years of a previous issue, the sample firms are biased towards big firms. We construct the variables size and book-to-market following Fama and French (2001) and put issuers in deciles based on the size deciles rank classified by year and exchange (NYSE/AMEX or Nasdaq) for all CRSP firms. Only 14.16% of our sample firms ranked in the bottom 50% of size of the firms in their exchanges. In contrast, book-to-market is more characteristic of the distribution of the universe of CRSP firms. The sample firms are roughly equally distributed across each book-to-market decile. As shown in Table II, about 69.96% (30.04%) of the firms has a book-to-market ratio in bottom (top) 50% book-to-market ratio of the firms in their exchanges.

(Insert Table II here)

[5] There are 1053 different firms represented in this reduced independent sample; 763 of these have only one issue in our sample, 167 firms have two issues in the sample, 123 have three or more (up to five) issues in our final sample.

We also compute the liquidity characteristics of our sample firms. Specifically, as our main liquidity metric we use the Amihud (2002) measure of illiquidity, which is defined as the average of the ratio of absolute returns over trading volume, measured at a daily frequency for non-zero volume days over the previous year:

$$Illiquidity_i = \frac{1}{Days_i} \sum_{t=1}^{Days_i} \frac{|Return_{it}|}{Volume_{it}}.$$

Amihud (2002) and Acharya and Pedersen (2005) describe this measure as an empirical characterization of the lambda parameter from the Kyle (1985) model, which captures the price pressure of trades.[6] One major advantage that the Amihud (2002) measure has over some other liquidity measures is that, because it is calculated using only CRSP data, it can be computed over more extensive sample periods than liquidity measures that require the Trades and Quotes (TAQ) data. Because the start of our sample in 1975 predates the TAQ data by almost 20 years, we favor the Amihud (2002) measure. Moreover, Hasbrouck (2005) shows that the Amihud (2002) measure is highly correlated with high-frequency measures of liquidity, so this seems to be a reasonable choice of experimental design. Each year we compute the ranks for the Amihud (2002) illiquidity measure for all firms in the CRSP database. Most of these debt-issuing sample firms are very liquid in the year prior to issue. More than 83.76% of our sample firms are more liquid than the median CRSP firm.

We also use other low-frequency liquidity measures, such as turnover, volume, and a variant on the Amihud (2002) measure where we use the ratio of absolute returns to turnover (instead of the more traditional method using volume in the denominator), and find very similar

[6] We compute our illiquidity measure using share volume rather than dollar volume. This mitigates concerns that illiquidity is changing over time due simply to inflation. Alternative ways to address this concern are to scale the illiquidity measure by changes in overall market capitalization or to scale the illiquidity measure by the cross-sectional mean illiquidity. Acharya and Pedersen (2005) use the former method; Amihud (2002) uses the latter method.

results for each of these alternative measures of liquidity. Because the alternative measures all tell the same story, we do not report these robustness tests in a table.[7]

We then show distributions of credit risk ratings of the debt issues in our sample. The bond ratings we use are from Standard and Poor's if they are available. If Standard and Poor's ratings are unavailable, we use Moody's ratings, and if neither of them is available we treat the bond as not rated. In our sample, about 62.07% of the bonds issued have a rating with BBB- or above (investment grade) while 37.93% bonds have ratings below BBB- (speculative grade).

II. Research Design

A. Control Firms

To find benchmark firms, we first start by constructing a portfolio formed of size and book-to-market matched non-issuing firms. We also restrict that the matched firms do not have debt offerings within five years before or after the offering date of the corresponding sample firms. Throughout the paper, in all of our matching procedures we match on exchange as well as any other matching criteria, even if we do not explicitly state as much. At the end of each year, we compute the size and book-to-market for all NYSE/AMEX firms. We then classify all public firms that do not have a debt offering in the past five years or future five years into ten size portfolios and then each size decile is subdivided into ten deciles of book-to-market ratio. Therefore, we have one hundred portfolios. We determine which of the one hundred portfolios each sample firm would be in, and then choose as the best match in that portfolio the firm that minimizes the sum of squared percentage differences of size and book-to-market. We proceed in

[7] The robustness of our results to using alternative measures such as turnover and volume is important for the interpretation of the results, because the Amihud (2002) measure could be simply serving as a proxy for a priced measure of risk such as idiosyncratic risk. However, the ultimate implication of our findings, that debt issuers do not underperform, remains unchanged regardless of the interpretation of what the Amihud (2002) measure captures.

identical fashion for Nasdaq listed issuers, using size deciles based on Nasdaq only. If our matched firms do not have stock return information from CRSP for sixty months after the corresponding sample firm issue date, for example, due to delisting prior to end of the sixty month period, we use the return from the next closest matched firm for the rest of period.

B. Buy-and hold returns

We measure the long-run stock returns following debt offering using the buy-and-hold return (BHR) approach. The BHR is calculated as:

$$BHR_i = \left[\prod_{t=1}^{T} (1 + R_{it}) - 1 \right] \times 100$$

where t = 1 is the first month following the debt offering, R_{it} is the return of month t following debt offering for firm i and T is the end of time horizon to compute the BHR or the delisting date, whichever comes earlier.

III. Why is Liquidity Different for Issuers and Matched Firms?

In addressing whether liquidity differences between debt issuers and matched firms can explain long-run stock performance of debt issuers, one question that should also be addressed is *why* there are liquidity differences between sample and matched firms. We turn to this question first, and show that our sample firms are relatively liquid and our matched firms are relatively illiquid because there is self-selection in which firms choose to issue debt, and this self-selection is driven by liquidity.

A. Probit tests: Are liquid firms more likely to appear in the sample?

Using a probit regression we directly address the question of whether liquidity affects the probability of a public debt issue and hence the likelihood of appearing in our sample. We identify as a sample of potential public debt issuer observations all firm-years in the universe of the intersection of CRSP and Compustat firms from 1974 through 1998 (non-financial and non-utility firms only). Debt issuer observations are those firm-years in which the firm has a public straight debt or convertible debt issue in the SDC database between 1975 through 1999 (that is, the CRSP and Compustat data is lagged one year).[8] We code public debt issue firm-years as 1, and non-issue firm-years as 0. Suppose firm *j* has a straight debt issue in 1980, no debt issue in 1981, and a convertible debt issue in 1982; we code such a firm as 1, 0, and 1, respectively for 1980, 1981, and 1982. Note that we revert back to our full sample that includes debt issue observations within five years of each other because we do not need the multi-year post issue stock returns for these tests. Thus, we have a panel (unbalanced) of observations. We estimate a random effects probit model where the dependent variable is our {0, 1} indicator for a public debt issue. Our results are qualitatively unchanged if we use a fixed effects logit, a pooled probit, or pooled logit model. We present the random effects probit regression results in Table III.

(Please insert Table III here)

Our right-hand side variables are the one-year lagged natural logarithm of the Amihud (2002) illiquidity measure and several control variables (lagged and similar to the variables in Denis and Mihov (2003)) that are intended to capture other aspects of the debt issuance choice: fixed assets ratio, firm size (logged market value of equity), profitability (average of EBITDA/total assets over the three years prior to debt issuance), market-to-book ratio, leverage (short-term + long-term debt / total assets), Altman's Z-score, beta, and an indicator variable for

[8] We are interested in examining whether liquidity affects the likelihood of being in our sample. Thus, we treat a year in which a firm increases its *private* borrowing (but does not have a public debt issue) as a non-issue observation since private financing events are not in our sample. The broader question of how firms choose among sources of debt financing is addressed empirically by Denis and Mihov (2003), among others. Dichev and Piotroski (1999) document underperformance by public straight and convertible debt issuers, but not by private debt issuers. This is consistent with our finding that public debt issuers have more liquid stock than counterparts that do not issue public debt.

whether the firm has an existing debt rating below BBB- (i.e., speculative grade). Requiring the last of these restricts the sample size to those firms that have an existing rating.

In each of our regression specifications, liquidity is a statistically significant predictor of year-ahead public debt issues: illiquid firms are significantly less likely to issue public debt. The liquidity effect is stronger for firms that have an existing debt rating. The coefficient on the illiquidity variable roughly doubles when we include our dummy variable for an existing speculative grade debt rating. Our interpretation is that firms with an existing rating have good access to public debt markets, and liquidity matters more at the margin for these firms.

Overall, the evidence in Table III shows that liquidity of the firm's stock affects the probability the firm issues public debt. This means that liquid firms are more likely to be sample firms. Thus, tests of the long-run stock performance of debt issuers are misspecified if they do not control for liquidity.

B. Differences in liquidity between sample firms and size and book-to-market matched firms

The probit model indicates that liquid firms are more likely to be debt issuers. In this section we document the magnitude of the liquidity differences between public debt issuers and benchmark firms matched by size and book-to-market. At first blush, one might think that both size and book-to-market would be related to liquidity, and so matching on these two factors should mitigate any differences in stock market liquidity. Both book-to-market and size, as measured by market value of equity, may proxy for firm transparency and hence may be correlated with stock market liquidity. Further, as mentioned above, all of our matching procedures also match on exchange, and this should further reduce differences in liquidity. Nonetheless, we find that significant differences in liquidity still exist.

In Table IV we break down the sample into subgroups so we can see where post-event liquidity differences between sample firms and their size and book-to-market matched peers are most severe.[9] We report mean values of *Amihud*$*10^6$ and ln(*Amihud*) for twelve subsets of sample firms and size and book-to-market matched firms, the difference of means, and p-values for a t-test of difference of means. Medians are qualitatively similar, and so are not reported in the table. For both measures, in each of the twelve categories of issuers the sample firms have higher mean liquidity than corresponding group of size and book-to-market matched peers. Of these twelve, ten have statistically significant differences in liquidity for both liquidity measures. The only groups that have statistically insignificant differences are issuers of investment grade straight debt and Nasdaq-listed issuers of straight debt.

(Please insert Table IV here)

The differences are largest in magnitude for convertible issuers, speculative convertible issuers, Nasdaq-listed issuers, and Nasdaq-listed convertible issuers. These groups have differences in *Amihud*$*10^6$ of -6.32, -7.72, -12.11, and -15.95, respectively, versus an overall average difference of -2.55, and differences in ln(*Amihud*) of -0.60, -0.61, -0.56, and -0.71 versus an overall average difference of -0.26.

C. Why are liquid firms more likely to appear in the sample?

The analysis in the sections above shows that liquid firms are more likely to issue public debt and hence are more likely to appear in our sample and that sample firms are systematically and substantially more liquid than benchmark firms matched on size and book-to-market. In this section, we discuss two reasons why this selection bias might occur.

[9] The differences in liquidity between sample and matched firms are significant for the full sample as well as the sub-samples we discuss in this section. Further, the average liquidity difference between sample firms and matched firms persists and somewhat increases for several years after the issue. Details are available from the authors upon request.

First, a firm's stock market liquidity is related to its credit quality on average, and the firm's credit quality is related to the likelihood of issuing bonds. A recent paper by Odders-White and Ready (2006) documents a contemporaneous and predictive relation between several traditional proxies for stock market liquidity and bond ratings. They find that firms with high liquidity have favorable bond ratings and firms with low liquidity have worse bond ratings. This relation is also apparent in our sample, as issuers of speculative grade debt have higher illiquidity measures than issuers of investment grade debt (Table IV). Denis and Mihov (2003) find that, conditional upon raising debt financing, firms with worse credit quality are more likely to issue private debt instead of public debt (and thereby, not being eligible for inclusion in our sample). Of course, another alternative that is open to low credit quality firms is not borrowing more from any source, which would also exclude them from our sample. On average, firms with worse credit quality face higher costs of debt (for example, see Kliger and Sarig (2000) and cites therein). Because firms with low liquidity are more likely to have poor bond ratings (conditional upon issuing debt), we should expect that those firms may be reluctant to issue public debt, and therefore illiquid firms would be less likely to become sample firms.

Second, security issuance costs can be related to stock market liquidity. Butler, Grullon, and Weston (2005b) show that investment bank gross spreads in seasoned equity offerings are related to the liquidity of the stock.[10] Over their entire sample, an increase in liquidity from the bottom to the top quintile would predict a decrease in gross spreads of about 101 basis points, or 21% of the mean spread, ceteris paribus. We gather from the SDC New Issues database the gross spreads for bonds that our sample firms issue to examine whether a similar relationship exists between stock liquidity and bond gross spreads. Note that "gross spread" denotes the

[10] Butler, et al. (2005b) use a variety of measures of liquidity, focusing primarily on a liquidity index that they construct from seven individual liquidity metrics. They do not use Amihud's (2002) measure of illiquidity.

percentage of proceeds that is paid as a fee to the investment banks; this is not to be confused with "spreads" denoting the difference between the bond's yield and a treasury security or with "spreads" denoting difference between bid and ask prices. In similar fashion to Butler, et al. we regress gross spreads for our sample firms on a measure of illiquidity (natural logarithm of the Amihud (2002) measure) and a number of control variables: natural logarithm of offer proceeds, lead manager market share of bond underwriting during the year, natural logarithm of the issuing firm's market value of equity orthogonalized to ln(*Amihud*) and dummies denoting speculative grade issues, Nasdaq listing of the equity, convertible bonds, and issues with a single bookrunner. Our results are very similar to those of Butler, et al. Our focus is on the coefficient on ln(*Amihud*), which takes a value of 0.1008 and is statistically significant at the 1% level. Transforming ln(*Amihud*) to a zero mean, unit variance variable produces a coefficient of 0.183, which means a one standard deviation change in ln(*Amihud*) produces a change in gross spread of 18.3 basis points. We present this result in Table V.[11]

(Please insert Table V here)

For direct comparison to the results Butler, et al. report, we compute that over our full sample an improvement in liquidity from the mean ln(*Amihud*) in its first quintile to the mean ln(*Amihud*) in its fifth quintile would predict a decrease in gross spreads of about 56 basis points, or roughly 36% of the mean spread of 1.55%, ceteris paribus. Thus, our estimate of the sensitivity of bond underwriting fees to liquidity is smaller in absolute terms (i.e., basis points), but larger in relative terms (i.e., as a percentage of the mean).

[11] Table V presents detailed statistics only for our main focus: the coefficient on the ln(*Amihud*) variable. The unreported coefficients on our control variables are broadly consistent with Butler, et al. For instance, we also find negative signs on firm size and issue size, and a positive sign on our Nasdaq indicator. In contrast to Butler, et al. we find a significant negative sign on investment bank reputation (their coefficient is insignificant) and a generally insignificant coefficient on our single bookrunner indicator (they find a significant negative sign on their multiple bookrunner indicator). We exclude some of their control variables, such as stock return volatility and stock price because they are not pertinent to bond issues. Our speculative grade debt indicator is positive and significant. The results are qualitatively unchanged by reasonable changes or modifications to the regression specification.

In addition to our full-sample tests, in Table V we estimate this regression separately for sub-samples of the data. The table shows that the sub-samples for which liquidity differences between sample firms and matched firms are the largest—convertible issuers, speculative grade issuers, Nasdaq-listed issuers—also are the sub-samples for which the sensitivity of gross spread to liquidity is the highest.[12] The coefficient on the standardized ln(*Amihud*) variable is 0.256 (0.157) for convertible (straight) debt issuers, 0.409 (0.216) for issuers of speculative (investment) grade debt, and 0.260 (0.167) for issuers listed on Nasdaq (NYSE or Amex). Thus, a one standard deviation increase in illiquidity for an issuer in, say, the convertible debt sub-sample would have an estimated increase in gross spread of 25.6 basis points, ceteris paribus. Thus, not only is liquidity a factor in bond offering gross spreads, but these investment banking fees are more sensitive to illiquidity in exactly the groups that have the worst liquidity mismatches, which is consistent with the idea that sample firms will reflect a self-selection bias related to their liquidity. That is, a particular firm is more likely to be a sample firm precisely because it has better liquidity.

IV. Stock Performance of Debt Issuers

The liquidity differences between sample firms and matched counterparts is important because recent theory and evidence suggests that liquidity is a priced factor in equity returns, where greater liquidity corresponds with lower required returns (see, as one recent example, Acharya and Pedersen (2005)). Thus, the higher liquidity of sample firms could at least partially explain the apparent underperformance of sample firms relative to size and book-to-market

[12] We do not report estimates for more narrowly defined sub-samples (e.g., convertible *and* speculative) because of a paucity of observations. Nonetheless, the results for these groups are consistent with what we present here.

matched peers. In this section we examine whether liquidity differences are influencing the underperformance result.

A. Buy-and-hold returns: sample firms versus size and book-to-market matched firms

We first replicate the long run performance tests from Spiess and Affleck-Graves (1999). The top two rows of Table VI present the differences in five-year buy-and-hold returns for sample firms versus size and book-to-market matched firms following debt offerings.[13] The difference in five-year buy-and-hold returns for straight debt issuers is -24% mean (statistically significant; $p < 0.01$) and -13% median (significant; $p < 0.01$). These differences are comparable to those reported by Spiess and Affleck-Graves. Our mean results are stronger than theirs, but our median results are slightly smaller in magnitude (they report for straight debt issuers a statistically insignificant mean difference of -14% and a significant median difference of -19%). For convertible issuers, we find differences in five-year buy-and-hold returns of -24% mean (statistically significant; $p = 0.08$) and -18% median (significant; $p = 0.03$). Spiess and Affleck-Graves (1999) document significant mean underperformance of convertible issuers of -37% and a median of -20%. Thus, the underperformance we find is comparable, but slightly less than what they find. Overall our findings based on size and book-to-market matched benchmark firms are broadly consistent with those of Spiess and Affleck-Graves (1999).

(Please insert Table VI here)

The other rows of Table VI present mean and median five year buy-and-hold returns for subgroups of the overall sample. First we segregate the sample into those straight debt issues that are speculative versus investment grade, and likewise for convertible issues. Next we

[13] In untabulated results we also examine mean and median differences of buy-and-hold returns at one-year, two-year, three-year, and four-year horizons. The results are consistent with the five-year results we discuss here, and indicate that statistically significant underperformance exists at shorter horizons as well. We focus our discussion on the five-year horizon returns to maintain consistency with Spiess and Affleck-Graves (1999). These additional results are available from the authors on request.

segregate the sample into those issuers whose stock is listed on Nasdaq versus those who are listed on NYSE/AMEX. We then further segregate the sample into only issuers of straight debt whose stock is listed on Nasdaq versus NYSE/AMEX and likewise for convertible debt issuers. Underperformance is most concentrated among speculative grade issuers and Nasdaq-listed issuers. Issuers of speculative grade straight debt have mean underperformance of -34% versus -17% for investment grade straight debt. Similarly, issuers of speculative grade convertible debt have mean underperformance of -26% versus -15% (insignificant; p = 0.29) for issuers of investment grade convertible debt. Nasdaq-listed issuers have mean underperformance of -79% versus -14% for NYSE/AMEX issuers. The magnitude of the Nasdaq return is driven in part by outliers—the median five year abnormal return is still large, but a slightly more modest -38%.

Interestingly, the groups with the most egregious underperformance are those with largest liquidity mismatches relative to benchmark firms. Since many authors find that liquidity is priced in the cross-section of stock returns, this raises the question of whether the underperformance can be explained by controlling for liquidity differences.

B. Calendar time returns

Fama (1998) points out that using an inappropriate model to estimate abnormal returns can lead to significant bias in long-run event studies. Mitchell and Stafford (2000) and Schultz (2003) also advocate rolling calendar time regressions to mitigate statistical problems that can arise in event-time tests. Specifically, Mitchell and Stafford (2000) show that one potential danger in long-run event studies is that long-run returns can be cross-correlated. If statistical tests incorrectly assume independence across observations, standard errors can become deflated, thereby inflating estimates of statistical significance. Schultz (2003) argues that the endogeneity of corporate events to stock prices (e.g., security issues might be more likely when stock prices are high) can also contaminate tests of underperformance. Calendar time tests can mitigate both of these problems.

In Table VII we use the Fama and French (1993) three-factor model based on calendar time measures of long-run buy-and-hold returns. For each month from 1975 through 1999, we compute the equal weighted return and the value weighted return for all issuers that have a public debt offering within past sixty months. We subtract the one-month Treasury bill rate to get portfolio excess return. We then regress the excess return on Fama-French's size, book-to-market and market risk factors. The intercept in these regressions reflects average monthly abnormal returns after controlling for other factors.

(Please insert Table VII here)

The regression model produces R-squared statistics of 87% when the dependent variable is the excess returns on the equal weighted portfolio of sample firms, and 91% when using the excess returns on the value weighted portfolio of sample firms. We find no significant underperformance of the value weighted portfolio ($p = 0.382$), which is consistent with the results Spiess and Affleck-Graves (1999) report. However, in the regression using the equal weighted portfolio of sample firms, the intercept is negative and statistically significant. The magnitude of the coefficient is -21 basis points per month ($p = 0.051$), which corresponds with underperformance of about -11.85% over a five-year horizon. These results are consistent with the calendar time results reported by Spiess and Affleck-Graves (1999); they find abnormal returns of -29 basis points per month for straight debt issuers and -31 basis points for convertible debt issuers. They are also consistent with our event time results, where median underperformance is roughly -14% overall (-13% for straight debt issuers and -18% for convertible issuers).

Thus, even in calendar time tests the underperformance of debt issuers can be statistically significant and economically non-trivial. This is important because it casts doubt on some alternative hypotheses—specifically, the inflated statistical significance brought about by cross-correlated long run returns (Mitchell and Stafford (2000)) and the endogeneity of the event process to previous returns (Schultz (2003)). In the next section we examine the hypothesis that the size and book-to-market matched firm benchmark we are using biases our results toward finding significance; i.e., we explore in depth the possibility that these results arise due to a bad model problem.

C. Event time tests: The effects of matching on liquidity on relative buy-and-hold returns

We continue our examination of the bad model problem by examining whether the systematic differences in stock market liquidity between sample firms and firms matched on size and book-to-market are economically important enough to materially affect the differences in buy-and-hold returns between sample firms and size and book-to-market matches. Our first approach is to add a matching criterion. Specifically, we now match on size, book-to-market, and *illiquidity* as measured by Amihud's (2002) measure as described above. (We note that matching on other liquidity metrics, such as average share turnover gives qualitatively very similar results, and so those results are not presented separately in a table.) In these tests the matched firms are picked based on the minimum of sum of squared percentage differences of size, book-to-market, and the Amihud (2002) illiquidity measure at the end of the year *preceding* the issue. As always, we also match on exchange.

Table VIII replicates Table VI, but uses our additional criterion of matching on pre-issue liquidity for forming the matched sample. Whereas in Table VI there are many categories of issuers that have severe underperformance relative to their matches, here almost all of that underperformance is gone. What is most noticeably absent is the severe underperformance of the worst-performing groups: the Nasdaq-listed issuers, the convertibles issuers, and the speculative grade issuers. All of these groups now have statistically insignificant underperformance relative to liquidity, size, and book-to-market matched peers, and some groups overperform (though insignificantly so). For instance, the mean five-year underperformance of the convertible issuers relative to matched firms is -24% if benchmark firms are matched only on size and book-to-market, but the abnormal performance is -12% and statistically insignificant (p = 0.18) if benchmark firms are also matched on liquidity. Similarly, the mean underperformance of the Nasdaq-listed issuers relative to matched firms is -79% if benchmark firms are matched only on size and book-to-market, but -18% and statistically insignificant (p = 0.17) if benchmark firms are also matched on liquidity. Likewise, the mean underperformance of the Nasdaq-listed straight debt issuers (the worst performing subgroup from Table VI) relative to matched firms is -118% if benchmark firms are matched only on size and book-to-market, but a statistically insignificant -17% (p = 0.17) if benchmark firms are also matched on liquidity. The lone disconnect is the group issuing speculative convertibles, whose mean is a statistically significant -19% (p=0.08). However, the median for this group is insignificantly different from zero.

(Please insert Table VIII here)

Collectively, this evidence shows that matching on liquidity has a dramatic effect on inferences of underperformance of these previously worst-performing groups. The magnitude of this liquidity effect is in line with what the asset pricing literature finds. The magnitude of the underperformance of our full sample goes from roughly -24% over five years (mean, based on size and book-to-market matching) to roughly -5.5% over five years (mean, when matching on liquidity also), which is a difference of about 18.5%. Based on Table 5 in Fujimoto and

Watanabe (2006), moving from the top thirty percent to the bottom thirty percent of liquidity corresponds to roughly the same magnitude of difference in returns (about -32 basis points per month across both states) when transformed to a five-year return (-32 basis points * 60 months = -19.2%). Thus, our findings support the idea that liquidity is an important matching criterion and a key component of these firms' cost of equity capital.

D. Calendar time returns with a liquidity factor

In this section we return to our calendar time regression tests, but now we explicitly control for liquidity in our tests. Since the sample firms are more liquid than matched firms, the matched firms have higher expected returns than the sample firms. This may cause the appearance of negative abnormal performance of sample firms if we do not control for liquidity. In Table IX we replicate our calendar time regression tests from Table VII, but following Eckbo and Norli (2005), we add a liquidity factor to the Fama-French three factor model.

To construct the liquidity factor (LMH), we start in 1975 and form two portfolios based on a ranking of the end-of-year market value of equity for all NYSE/AMEX stocks. Next in each size portfolio, we form three portfolios using NYSE/AMEX stocks ranked on Amihud's (2002) illiquidity measure. Monthly value-weighted returns on these six portfolios are calculated starting in January 1975. Portfolios are reformed in January every year using rankings from December the previous year. The return on the LMH portfolio is the difference between the equal-weighted average return on the two portfolios with high Amihud (2002) measure and the equal-weighted average return on the two portfolios with low Amihud (2002) measure. We then repeat this procedure using average share turnover as our liquidity metric.

(Please insert Table IX here)

Table IX presents the regression results with an additional liquidity factor. In the first two regressions we use a liquidity factor constructed from the Amihud (2002) illiquidity factor. In the second two regressions the liquidity factor is based on average share turnover. We use as the dependent variable either the excess returns on an equal weighted calendar time portfolio of sample firms or the excess returns on a value weighted calendar time portfolio of sample firms. In each of the four regressions, the intercept is statistically insignificant. The magnitude of the coefficient ranges from -18 basis points per month to +0.2 basis points per month. This shows that controlling for a liquidity factor in equity returns is sufficient to erase the long-run underperformance of straight debt and convertible debt issuers. (We note that we find comparable results using Pastor and Stambaugh (2003) value-weight and equal-weight liquidity risk factors.)

V. Conclusion

There is substantial debate over the long run performance of stock returns following various corporate events. Our paper enters this fray with a reexamination of the long run performance of debt and convertible debt issuing firms. We use a large and updated sample of debt and convertible debt issuers and come to very different conclusions than what the literature currently provides. We argue that the underperformance of debt issuers is not driven by the problems inherent in event-time tests—notably, the biased standard errors that arise from cross-correlation among observations (Mitchell and Stafford (2000)) and the pseudo market timing problem (Schultz (2003))—because negative abnormal returns still appear in calendar time unless we include liquidity as a factor in our calendar time regressions. Instead, the evidence is consistent with a bad model problem—sample firms are systematically different than traditional benchmark firms in that they are substantially more liquid.

Our results show that liquidity differences between size and book-to-market matched firms are large, especially for the subgroups that have the largest apparent underperformance. Recent work has shown that liquidity affects security returns, and we show that this omitted factor impacts the inferences of long-run performance of sample firms relative to poorly matched benchmark firms. Specifically, because sample firms have significantly higher liquidity than size and book-to-market matched peers, they *should* have lower required returns and as a result, there is no underperformance once sample firms are properly benchmarked. We believe that, in its entirety, the evidence here is consistent with there being *no systematic underperformance* by debt-issuing firms relative to proper benchmarks. At the very least, our evidence shows that the results that debt and convertible debt issuers underperform in the long run are very sensitive to the benchmark that is used.

Our findings add to the growing literature that documents the importance of market microstructure considerations on asset pricing and corporate finance applications. The findings here also suggest that researchers should carefully consider additional asset pricing model factors and matching criteria other than size and book-to-market when studying long-run stock performance around corporate events.

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Table I
Distribution of Debt Offerings by Calendar Year and Bond Type

The sample includes straight debt and convertible debt offerings reported in *SDC New Issues Database* over the period 1975 to 1999 that meet the following criteria: (1) The company is listed on the NYSE, AMEX or Nasdaq exchange at the time of the issue; (2) the company is not a regulated utility or a financial institution; (3) the shares traded for the company are ordinary common shares (ADRs, SBIs, REITs, and closed-end funds are omitted); (4) the issue does not include warrants; (5) the company is included in both the CRSP and Compustat databases and (6) the company has sixty month return after the issue and has matched non issue firms. We exclude issues that occur within five years after a previous straight debt or convertible debt offering.

Year	Straight Debt Offerings	Convertible Debt Offerings
1975	57	8
1976	14	2
1977	11	1
1978	13	0
1979	15	2
1980	33	17
1981	10	16
1982	22	7
1983	15	20
1984	13	12
1985	41	24
1986	45	47
1987	32	26
1988	24	9
1989	9	18
1990	18	11
1991	49	17
1992	53	21
1993	62	14
1994	21	5
1995	41	2
1996	49	12
1997	52	6
1998	63	1
1999	37	5
Total	799	303

Table II

Distribution of Debt Offerings by Size, Book-to-Market and Bond Rating

The sample includes straight debt and convertible debt offerings reported in *SDC New Issues Database* over the period 1975 to 1999 that meet the following criteria: (1) The company is listed on the NYSE, AMEX or Nasdaq exchange at the time of the issue; (2) the company is not a regulated utility or a financial institution; (3) the shares traded for the company are ordinary common shares (ADRs, SBIs, REITs, and closed-end funds are omitted); (4) the issue does not include warrants; and (5) the company is included in both the CRSP and Compustat databases. We exclude issues that occur within five years after a previous straight debt or convertible debt offering. All deciles for sample firms are computed separately by exchange (NYSE/AMEX or Nasdaq) from all CRSP firms. Size and book-to-market rank is based on the end of the prior fiscal year when the debt offering is issued. Liquidity is computed as the inverse of the Amihud (2002) illiquidity measure, where illiquidity is the average of the ratio of daily absolute return to daily trading volume; the liquidity rank is based on the year prior to the event. Deciles are updated every year. The bond rating is from S&P, and Moody's when an S&P rating is not available.

Panel A: Size, Book-to-market, Liquidity

	Size		Book-to-Market		Liquidity	
Decile	Frequency	Cumulative percent	Frequency	Cumulative percent	Frequency	Cumulative percent
Smallest (Illiquid)	4	0.36	163	14.79	8	0.73
2	11	1.36	175	30.67	20	2.54
3	32	4.26	168	45.92	36	5.81
4	43	8.17	142	58.8	42	9.62
5	66	14.16	123	69.96	73	16.24
6	94	22.69	103	79.31	110	26.23
7	117	33.3	82	86.75	116	36.75
8	159	47.73	57	91.92	170	52.18
9	223	67.97	53	96.73	201	70.42
Biggest (Liquid)	353	100.00	36	100.00	326	100.00

Panel B: Bond Ratings

Bond Rating	Frequency	Cumulative percent
AAA	31	2.81
AA	130	14.61
A	300	41.83
BBB	223	62.07
BB	111	72.14
B	239	93.83
CCC and below	68	100.00

Table III
Random Effects Probit Regression Predicting the Issuing of Public Debt

The sample includes all non-utility and non-financial firms over 1974 to 1998 from CRSP and Compustat database. We estimate the following regression equation over the full sample of available data and over sub-samples of the data: $Public\ Debt\ Issue_{i,t} = \alpha + \beta \mathrm{Ln}(Amihud_{i,t-1}) + \gamma Controls_{i,t-1} + \varepsilon_{i,t}$. The dependent variable is a dummy equal to 1 if the firm, as identified from the *SDC New Issues Database,* has any straight debt or convertible debt offerings reported at year *t*, zero otherwise. The *Amihud* illiquidity measure is computed as in Amihud (2002): the average ratio of daily absolute return to same day trading volume over the year *t*-1. The fixed assets ratio is the ratio of property, plant and equipment to total assets (TA). Profitability is defined as the average ratio of EBITD/TA over year *t*-3 to year *t*-1, three years prior to issuance. Size is the end of year close price multiplied by outstanding shares. The market-to-book ratio is the size divided by the book value that is sum of book equity plus deferred tax. Leverage is the sum of short-term and long-term debt, divided by total assets. Altman's Z-score is calculated as *Z=1.2(Working Capital/Total Assets) + 1.4(Retained Earnings/Total Assets) + 3.3(Earnings Before Interest and Taxes/Total Assets) + 0.6(Market Value of Equity/Book Value of Liabilities) + 0.999(Net Sales/Total Assets).* Beta is the *t*-1 year-end beta value of the firm from CRSP. The speculative grade rating is an indicator variable equal to one if the firms have an existing debt rating of below BBB, and zero otherwise. Coefficients are reported with p-values in parentheses below. Statistically significant coefficients appear in **bold**.

Model	(1)	(2)	(3)	(4)
Log(Amihud)	**-0.077**	**-0.076**	**-0.035**	**-0.044**
	(0.004)	(0.004)	(0.015)	(0.002)
Fixed asset ratio	0.201	0.201	**0.519**	**0.507**
	(0.159)	(0.158)	(0.000)	(0.000)
Profitability	0.095	0.094	**0.699**	**0.728**
	(0.819)	(0.820)	(0.000)	(0.000)
Log(size)	**0.288**	**0.288**	**0.324**	**0.318**
	(0.000)	(0.000)	(0.000)	(0.000)
Market-to-book ratio	**-0.016**	**-0.016**	**-0.028**	**-0.028**
	(0.079)	(0.079)	(0.000)	(0.000)
Leverage	**0.545**	**0.544**	**0.933**	**0.938**
	(0.020)	(0.021)	(0.000)	(0.000)
Altman's Z-score	**-0.045**	**-0.045**	**-0.027**	**-0.026**
	(0.002)	(0.002)	(0.000)	(0.000)
Beta	-0.005		**0.083**	
	(0.912)		(0.001)	
Speculative grade rating	-0.106	-0.106		
	(0.139)	(0.139)		
Constant	**-4.708**	**-4.709**	**-5.026**	**-5.052**
	(0.000)	(0.000)	(0.000)	(0.000)
N	11578	11582	70434	71027

Table IV

Liquidity for Sample Firms and Size and Book-to-Market Matched Firms

The sample includes straight debt and convertible debt offerings reported in *SDC New Issues Database* over the period 1975 to 1999 that meet the criteria described above in Table II. Our illiquidity measures are computed as in Amihud (2002): the average ratio of daily absolute return to same day trading volume, averaged over the five years following issuance. We then transform the Amihud measure by multiplying it by one million (left columns) or by taking the natural log (right columns). Investment grade bonds are those with ratings of at least BBB- or Baa3; speculative grade bonds are those with ratings worse than investment grade. We report p-values for difference of means tests for the sample firms and benchmark firms that are matched on size and book-to-market. Statistically significant differences are marked in **bold**.

		Mean *Amihud* X 10^6			Mean Ln(*Amihud*)		
	N	Sample Firms	Size, Book-to-Market, Exchange Matched Firms	Difference (p-value)	Sample Firms	Size, Book-to-Market, Exchange Matched Firms	Difference (p-value)
All Straight Debt	799	1.33	2.45	**-1.12**	-15.65	-15.51	**-0.14**
				(0.01)			(0.00)
All Convertible Debt	303	4.95	11.27	**-6.32**	-14.21	-13.61	**-0.60**
				(0.00)			(0.00)
Straight & Investment	616	0.43	0.81	-0.39	-16.14	-16.09	-0.05
				(0.15)			(0.25)
Straight & Speculative	171	4.00	7.31	**-3.31**	-14.07	-13.62	**-0.45**
				(0.05)			(0.00)
Convertible & Investment	68	0.54	2.06	**-1.52**	-15.52	-14.94	**-0.59**
				(0.02)			(0.00)
Convertible & Speculative	235	6.22	13.94	**-7.72**	-13.83	-13.22	**-0.61**
				(0.00)			(0.00)
All NYSE/Amex	923	1.22	1.91	**-0.69**	-15.53	-15.32	**-0.21**
				(0.00)			(0.00)
All Nasdaq	179	8.05	20.16	**-12.11**	-13.82	-13.26	**-0.56**
				(0.00)			(0.00)
NYSE/Amex & Straight	728	0.97	1.59	**-0.61**	-15.78	-15.66	**-0.12**
				(0.02)			(0.00)
Nasdaq & Straight	71	4.99	11.28	**-6.29**	-14.38	-14.05	-0.33
				(0.11)			(0.12)
NYSE/Amex & Convertible	195	2.11	3.11	**-1.00**	-14.63	-14.08	**-0.54**
				(0.01)			(0.00)
Nasdaq & Convertible	108	10.06	26.00	**-15.95**	-13.45	-12.74	**-0.71**
				(0.01)			(0.00)

Table V
The Effect of Illiquidity on Investment Bank Gross Spreads

The sample includes straight debt and convertible debt offerings reported in *SDC New Issues Database* over the period 1975 to 1999 that meet the criteria described above in Table II and for which we have data for the investment banking gross spread. Our illiquidity measures are computed as in Amihud (2002): the average ratio of daily absolute return to same day trading volume, averaged over the five years following issuance. We then transform the Amihud measure by multiplying it by taking the natural log. Investment grade bonds are those with ratings of at least BBB- or Baa3; speculative grade bonds are those with ratings worse than investment grade. Nasdaq and NYSE/Amex refer to the trading venue of the firm's common stock. We estimate the following regression equation over the full sample of available data and over sub-samples of the data: $Gross\ Spread = \alpha + \beta \ln(Amihud) + \gamma Controls + \varepsilon$, where *Gross Spread* is the percent of the bond proceeds paid to investment bankers, *Amihud* is as defined in the tables above. *Controls* refers to a vector containing the following control variables: natural logarithm of offer proceeds, lead manager market share of bond underwriting during the year, natural logarithm of the issuing firm's market value of equity (i.e., size) orthogonalized to ln(*Amihud*) and dummies denoting (a) speculative grade issues, (b) Nasdaq trading of the equity, (c) bonds convertible into equity, and (d) issues with a single bookrunner. The appropriate dummies are omitted from the vector of controls in the sub-sample regressions (e.g., the Nasdaq variable is omitted in regressions of only Nasdaq or non-Nasdaq firms). The table reports the coefficient on the ln(*Amihud*) variable, its p-value, the coefficient on the standardized (zero mean, unit variance) ln(*Amihud*) variable, number of observations, regression R-squared. We do not report the coefficients for the control variables.

	Full Sample	Convertible Only	Straight Only	Speculative Grade Only	Investment Grade Only	Nasdaq Only	NYSE / Amex Only
ln(*Amihud*) Coefficient	0.1008	0.1524	0.0759	0.2023	0.0444	0.1300	0.0920
p-value	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
ln(*Amihud*) Coefficient (Standardized)	0.183	0.256	0.157	0.409	0.216	0.260	0.167
N	990	260	730	359	631	143	847
R-Squared	0.767	0.566	0.811	0.422	0.350	0.699	0.748

Table VI
Differences in Five-Year Buy-and-Hold Returns for Sample Firms and Size and Book-to-Market Matched Firms by Bond Rating, Exchange and Bond Type

The sample includes straight debt and convertible debt offerings reported in *SDC New Issues Database* over the period 1975 to 1999 that meet the following criteria described above in Table II. We report the mean and median differences of buy-and-hold returns at various horizons for sample firms and their size and book-to-market matched counterparts. Beneath the differences and in parentheses appear p-values for tests of the null hypothesis that the mean or median difference is zero. The difference of the means test is a t-test; the difference of medians is a Wilcoxon rank sum test. Significant differences are marked in **bold**. Investment grade bonds are those with ratings of at least BBB- or Baa3; speculative grade bonds are those with ratings worse than investment grade.

	N	Mean Difference in Returns Between Sample and Matched Firms	Median Difference in Returns Between Sample and Matched Firms
All Straight Debt Issuers	799	**-0.24**	**-0.13**
		(0.00)	(0.00)
All Convertible Debt Issuers	303	**-0.24**	**-0.18**
		(0.08)	(0.03)
Straight & Investment Bond	616	**-0.18**	**-0.08**
		(0.01)	(0.07)
Straight & Speculative Bond	171	**-0.46**	**-0.55**
		(0.01)	(0.00)
Convertible & Investment Bond	68	-0.15	-0.29
		(0.29)	(0.14)
Convertible & Speculative Bond	235	**-0.26**	**-0.16**
		(0.05)	(0.10)
All NYSE/AMEX	923	**-0.14**	**-0.11**
		(0.01)	(0.01)
All Nasdaq	179	**-0.79**	**-0.38**
		(0.00)	(0.00)
NYSE/AMEX & Straight Debt	728	**-0.15**	**-0.11**
		(0.01)	(0.01)
Nasdaq & Straight Debt	71	**-1.18**	**-0.46**
		(0.01)	(0.01)
NYSE/AMEX & Convertible Debt	195	-0.07	-0.15
		(0.34)	(0.40)
Nasdaq & Convertible Debt	108	**-0.54**	**-0.29**
		(0.06)	(0.02)

Table VII
Fama-French Three Factor Calendar-Time Portfolio Regressions
(Sample Matched by Size, Book-to-Market)

$$Y_t=\alpha + \beta(Rm_t\text{-}Rf_t\ )+\gamma_1(SMB_t\ )+\gamma_2(HML_t\ )+\varepsilon_t$$

The sample period is from February 1975 to December 1999 (299 months), and sample firm returns are included in a particular monthly portfolio if the firm's debt offering date occurred within the last 60 months. Rm_t is the return on the value-weighted index of NYSE, Amex, and Nasdaq stocks in month t; Rf_t is the 1-monthT-bill yield in month t; SMB_t is the return on small firms minus the return on large firms in month t; and HML_t is the return on high book-to-market stocks minus the return on low book-to-market stocks in month t. The factor definitions are described in Fama and French (1993). In regression (1), the dependent variable is the excess return on the equally weighted portfolio of sample firms, $R_{p(EW)}$-R_f. In regression (2), the dependent variable is the excess return on the value weighted portfolio of sample firms, $R_{p(VW)}$-R_f. The five-year cumulative abnormal return is computed from the constant from the regression. P-values based on White's (1980) heteroskedasticity robust standard errors appear in parentheses. All significant intercepts are marked in **bold**.

	(1)	(2)
	$R_{p(EW)} - R_f$	$R_{p(VW)} - R_f$
Excess Return on the Market(Rm_t-Rf_t)	1.167	1.035
	(0.000)	(0.000)
Small-Minus-Big Return (SMB_t)	0.247	-0.125
	(0.000)	(0.000)
High-Minus-Low Return (HML_t)	0.335	0.020
	(0.000)	(0.541)
Constant	**-0.21%**	-0.07%
	(0.051)	(0.382)
Observations	358	358
Adjusted R-squared	87.07%	91.30%
Five-year cumulative abnormal return	-11.85%	-3.88%

Table VIII
Five-Year Buy-and-Hold Returns by Bond Rating, Exchange and Bond Type
(Sample Matched by Size, Book-to-Market and Liquidity)

The sample includes straight debt and convertible debt offerings reported in *SDC New Issues Database* over the period 1975 to 1999 that meet the criteria described above in Table II. We report the mean and median difference in the five-year buy and hold return for the sample firms versus size, book-to-market, exchange, and liquidity matched firms following the issue date. Illiquidity is measured following Amihud (2002), and is computed by averaging the ratio of daily absolute return to same day trading volume. The difference of the means test is a t-test; the difference of medians test is a Wilcoxon rank sum test. Both have as the null hypothesis that the mean (median) difference is zero. All p-values are reported in parenthesis below the returns and all significant differences are marked in **bold**. The bond rating is from S&P and Moody's when S&P rating is not available. We define bond as investment grade if the bond rating is BBB- or Baa3 or above, and speculative if the rating is below investment grade.

	N	Mean Difference in Returns Between Sample Firms and Size, Book-to-Market, and Liquidity Matched Firms	Median Difference in Returns Between Sample Firms and Size, Book-to-Market and Liquidity Matched Firms
All Straight Debt Issuers	799	-0.03	-0.07
		(0.31)	(0.48)
All Convertible Debt Issuers	303	-0.12	-0.12
		(0.18)	(0.19)
Straight & Investment Bond	616	0.02	-0.05
		(0.60)	(0.93)
Straight & Speculative Bond	171	-0.21	-0.17
		(0.12)	(0.20)
Convertible & Investment Bond	68	0.13	-0.03
		(0.76)	(0.79)
Convertible & Speculative Bond	235	**-0.19**	-0.13
		(0.08)	(0.11)
All NYSE/AMEX	923	-0.03	-0.07
		(0.29)	(0.46)
All Nasdaq	179	-0.18	-0.12
		(0.17)	(0.19)
NYSE/AMEX & Straight Debt	728	-0.02	-0.06
		(0.39)	(0.82)
Nasdaq & Straight Debt	71	-0.17	-0.30
		(0.23)	(0.21)
NYSE/AMEX & Convertible Debt	195	-0.08	-0.14
		(0.27)	(0.24)
Nasdaq & Convertible Debt	108	-0.19	-0.03
		(0.25)	(0.57)

Table IX
Fama-French Three Factor Calendar-Time Portfolio Regressions
(Sample Matched by Size and Book-to-Market)

$$Y_t=\alpha + \beta(Rm_t\text{-}Rf_t)+\gamma_1(SMB_t)+\gamma_2(HML_t)+\gamma_3(LMH_t)+\varepsilon_t$$

The sample period is from February 1975 to November 2004 (358 months), and sample firm returns are included in a particular monthly portfolio if the firm's debt offering date occurred within the last 60 months. Rm_t is the return on the value-weighted index of NYSE, Amex, and Nasdaq stocks in month *t*; Rf_t is the 1-monthT-bill yield in month t; SMB_t is the return on small firms minus the return on large firms in month t; and HML_t is the return on high book-to-market stocks minus the return on low book-to-market stocks in month t. The factor definitions are described in Fama and French (1993). LMH_t is the return on low liquidity stocks minus the return on high liquidity stocks in month t. To construct LMH, we start in 1975 and form two portfolios based on a ranking of the end-of-year market value of equity for all NYSE/AMEX stocks and three portfolios formed using NYSE/AMEX stocks ranked on the *Amihud* illiquidity measure. Next, six portfolios are constructed from the intersection of the two market value and the three *Amihud* portfolios. Monthly value-weighted returns on these six portfolios are calculated starting in January 1975. Portfolios are reformed in January every year using firm rankings from December the previous year. The return on the LMH portfolio is the difference between the equal-weighted average return on the two portfolios with low liquidity and the equal-weighted average return on the two portfolios with high liquidity. In regressions (1) and (2) liquidity is measured following Amihud (2002), and is computed by averaging daily absolute return divided by daily trading volume). In regressions (3) and (4) liquidity is measured as share turnover. In regressions (1) and (3), the dependent variable is the difference between equaled weight sample portfolio return and risk free rate, $R_{p(EW)}$-R_f; in regressions (2) and (4), the dependent variable is the difference between value weighted sample portfolio return and risk free rate, $R_{p(VW)}$-R_f; The five-year cumulative abnormal return is computed based on the monthly abnormal return equaling to the constant from the regression. Parameter estimates are presented with p-value in parentheses. All p-values are calculated using White's method (White, 1980). All significant intercepts are marked in **bold**.

	(1)	(2)	(3)	(4)
	Amihud	*Amihud*	*Turnover*	*Turnover*
	$R_{p(EW)}-R_f$	$R_{p(VW)}-R_f$	$R_{p(EW)}-R_f$	$R_{p(VW)}-R_f$
Excess Return on the Market(Rm_t-Rf_t)	1.151	1.024	1.014	1.024
	(0.000)	(0.000)	(0.000)	(0.000)
Small-Minus-Big Return (SMB_t)	0.269	-0.110	0.129	-0.110
	(0.002)	(0.000)	(0.053)	(0.000)
High-Minus-Low Return (HML_t)	0.354	0.032	0.359	0.032
	(0.000)	(0.370)	(0.000)	(0.370)
Low-Minus-High Liquidity (LMH_t)	-0.093	-0.061	-0.393	-0.061
	(0.413)	(0.284)	(0.000)	(0.284)
Constant	-0.18%	-0.05%	0.002%	-0.018%
	(0.115)	(0.529)	(0.983)	(0.830)
Observations	358	358	358	358
Adjusted R-squared	87.12%	91.33%	88.91%	91.42%
Five-year cumulative abnormal return	-10.46%	-2.96%	0.12%	-1.07%