Clientele Change, Liquidity Shock, and the Return on Financially Distressed Stocks

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Abstract

We show that the abnormal returns on high-default risk stocks documented by Vassalou and Xing (2004) are driven by short-term return reversals rather than systematic default risk. These abnormal returns occur only during the month after portfolio formation and are concentrated in a small subset of stocks that had recently experienced large negative returns. Empirical evidence supports the view that the short-term return reversal arises from a liquidity shock triggered by a clientele change.

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I. Introduction

The pricing of financial distress or default risk is one of the fundamental questions in financial economics. In a recent study, Vassalou and Xing (2004) measure default risk using a default likelihood indicator (DLI) computed according to the Black-Scholes (1973) and Merton (1974) option pricing framework and show that stocks more likely to default earn a higher return than otherwise similar stocks. Their finding represents a puzzle for the literature on financial distress or default risk, as most recent research documents the opposite relation (see Dichev (1998), Griffin and Lemmon (2002), Garlappi, Shu, and Yan (2007), Campbell, Hilscher, and Szilagyi (2007) and George and Hwang (2007)). We resolve this puzzle by relating Vassalou and Xing's finding to the short-term return reversal first documented by Jegadeesh (1990) and Lehman (1990). In addition, we analyze a concrete channel through which a liquidity shock might occur on a stock which in turn causes the return reversal.

The default risk premium documented by Vassalou and Xing (2004) appears rather high: the stocks in the highest default risk decile earn about 90 basis points (bps) more per month than otherwise similar stocks, with a monthly Sharpe ratio of around 0.25 between 1970 and 1999. This high default risk premium represents another puzzle, as Hansen and Jagannathan (1991) point out, the associated high Sharpe ratio cannot be easily explained in perfect and complete markets. For comparison, during the same period, the monthly return on the Fama-French HML factor (the return difference between high and low book-to-market stocks) is only 35 bps with a monthly Sharpe ratio of 0.13. In addition, this high default risk premium cannot be fully explained by the standard Fama-French (1993) three-factor model and a separate aggregate default risk factor seems to be needed.

To reconcile these two puzzling findings by Vassalou and Xing with the literature, our investigation first reveals that stocks in the highest-DLI decile earn abnormal returns only in the first month after portfolio formation. The return on these stocks immediately declines by more than a quarter, from 2.10% in the first month to 1.52% in the second month, and stabilizes afterward. If we skip a month and use the second-month returns in various asset pricing tests, we find that the returns of high-default risk stock can be fully explained by the Fama-French three-factor model, and the additional default risk factor is no longer needed. We also verify that characteristics such

as size, book-to-market ratio, default likelihood and loadings on risk factors barely change from the first to the second month after portfolio formation. Second, we show that abnormal returns on the highest DLI decile are confined to a small subset of stocks with similar DLIs that recently experienced large negative returns and sharp increases in their DLI measure (the high DLI losers). Thus the abnormal return on high-default risk stocks documented in Vassalou and Xing (2004) is temporary, and clearly does not represent compensation for bearing systematic default risk.

Empirically, high-default risk stocks are recent losers on average during the portfolio formation month, so their abnormal return in the subsequent month constitutes a short-term return reversal, a robust empirical regularity first uncovered by Jegadeesh (1990) and Lehman (1990). In a cross-sectional regression framework, we confirm that the past one-month return drives out DLI in predicting the next-month stock return.

What could be the possible causes of such short-term return reversal on default-risk stocks? The evidence suggests that it is likely the result of price pressure caused by a liquidity shock around portfolio formation. The link between short-run reversal and liquidity shock has been discussed by Campbell, Grossman, and Wang (1993), Conrad, Hameed, and Niden (1994) and more recently by Avramov, Chordia, and Goyal (2006). They find greater return reversals in high-turnover, illiquid stocks, and attribute such return reversals to non-information-based demands for immediacy. The changes in various liquidity characteristics of high-DLI stocks largely support such argument. Unlike the existing literature, however, we can identify at least one plausible economic reason behind such demands for immediacy on high-DLI stocks: a financial distress-induced clientele change.

Institutional investors are often confined to investment in stocks that are liquid, with large market capitalization and stable dividend payouts (see Almazan, Brown, Carlson, and Chapman (2004)). An increase in a stock's likelihood of default will trigger selling among institutional investors. A sudden change in the clientele for a stock triggers selling by one group of investors with no offsetting increase in the demand from other investors. This imbalance represents a liquidity shock, and market makers will have to step in and provide liquidity, earning substantial price concessions for providing immediacy. Prices will bounce back once outside investors recognize the opportunity and redeploy capital. We find that mutual funds and other institutions significantly reduce their holdings of stock in firms experiencing a sharp rise in their default likelihood measures.

Examination of a proprietary institutional trading dataset confirms significant institutional selling of such stocks.

Stocks associated with high default risk are likely to be penny stocks, and their average bid-ask spread as a percentage of trading price is relatively high. The bid-ask bounce could cause a sizable upward bias in average return computation, as noted by Blume and Stambaugh (1983) and recently by Bessembinder and Kalcheva (2007). Computation of the bid-ask bounce bias and recalculation of the monthly stock returns excluding the first trading day after portfolio formation both demonstrate that the abnormal return on high-DLI stocks is driven by more than just bid-ask bounce bias.

While De Long, Shleifer, Summers, and Waldmann (1990), Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that investor overreaction can also lead to return reversal, we believe that it is unlikely the main driver of the price reversal on the high DLI stocks. First, the close tie between the price reversal on high DLI stocks and the changes in their liquidity-related characteristics is more consistent with a price pressure explanation. Second, most behavioral models predict the impact of the behavioral bias to be stronger for stocks associated with information uncertainty (see Hirshleifer (2001) and Zhang (2006)). However, we fail to find stronger return reversals for stocks associated with higher degree of information uncertainty.

Our findings contribute to a growing literature on the relation between default risk and stock returns by reconciling Vassalou and Xing (2004) with other findings. Campbell, Hilscher, and Szilagyi (2007) examine annual return where short-term liquidity-induced return reversal plays a smaller role, while Garlappi, Shu, and Yan (2007) focus on second-month returns. As financially distressed stocks are usually small stocks and prone to liquidity shock, our findings thus highlight the importance of accounting for liquidity shocks in the empirical examination of default or financial distress risk. This is especially true when the default risk measure is computed directly using the market price of a stock.

Our findings also add to the literature that analyzes the impact of liquidity shocks on asset prices. Related work includes Grossman and Miller (1988) and Coval and Stafford (2007) among others. These authors argue that liquidity shocks have a large and persistent impact on asset prices, which we confirmed. The empirical challenge is to identify the economic mechanisms underlying such a liquidity shock. That is, why do agents decide to trade a large amount of particular assets

at the same time? We contribute in this regard by providing one plausible explanation: a sharp increase in default risk. When a stock experiences a sharp increase in default risk, financial institutions with binding investment restrictions have to sell the stock immediately, creating a liquidity shock.

Our finding of institutional selling during and immediately after large short-term negative returns also adds to a broader and more recent literature on individual and institutional trading behavior. Griffin, Harris, and Topaloglu (2003) document a net institutional selling after negative previous day stock returns in Nasdaq 100 securities, which is consistent with the institutional selling after negative returns that we observe at the monthly horizon. Kaniel, Saar, and Titman (2008) show that individual tend to buy NYSE stocks (inferring institutional selling) following declines in the previous month.

The remainder of the paper is organized as follows: Section II briefly reviews various proxies for default risk, in particular the default likelihood indicator (DLI) in Vassalou and Xing (2004). Section III shows that the abnormal returns on high-DLI stocks occur only during the first month after portfolio formation and is concentrated in a subset of high DLI losers. Section IV analyzes several possible causes of short-term return reversals on high DLI stocks and provide supporting evidence that it is likely a result of a clientele change. Section V concludes.

II. Brief Review of Default Risk Measures

Previous research have identified characteristics that are associated with default or financial distress risk. The most common characteristic is financial leverage. A long thread of literature on bankruptcy predictions consistently finds that financial leverage both economically and statistically significant in predicting the likelihood of bankruptcy. A more comprehensive survey on this topic can be found in Shumway (2001). Both systematic and idiosyncratic risk increases with financial leverage, *ceteris paribus*, and increases in such risk would be associated with increases in expected returns. Bhandari (1988) finds the expected stock returns are indeed positively related to debt-to-equity ratio, even after controlling for beta and size.

Most recently, researchers start to use various direct measures of default or financial distress risk. For instance, Dichev (1998), Griffin and Lemmon (2002) and George and Hwang (2007)

use accounting bankruptcy measures for distress risk such as Altman's (1968) Z-score and Ohlson's (1980) O-score; Garlappi, Shu and Yan (2007) use Moody's KMV's expected default frequencies^{TM}; Campbell, Hilscher, and Szilagyi (2007) consider their own version of default predictor. In all of these studies, default or financial distress risk is shown to be negatively associated with stock returns especially when the default risk is higher.

One criticism of accounting-based measures for estimation of default risk is that accounting information is updated infrequently. To deal with this problem, Vassalou and Xing (2004) estimate a default likelihood indicator (DLI) in the Black-Scholes (1973) and Merton (1974) framework for each firm as:

$$DLI = N\left(-DD\right) = N\left(-\frac{\ln(V_A/X) + (\mu - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right) \tag{1}$$

where $N(\cdot)$ is the normal cumulative distribution function; DD is distance to default; X and T are the face value and the maturity of the firm's debt, respectively; V_A is the value of the firm's assets; and μ and σ_A are the instantaneous drift and volatility of the firm's assets, respectively. V_A, μ, and σ_A are estimated iteratively using daily stock returns of the past year.

The main advantage of using DLI is that it uses market price information that is updated more frequently than credit ratings or other accounting default measures, so it should be a better measure for predicting bankruptcy. Vassalou and Xing (2004) show that DLI predicts actual defaults well. This is confirmed by Hillegeist, Keating, Cram, and Lundstedt (2004), who compare a slightly modified version of DLI and traditional accounting measures — the Z-score and O-score — and find DLI to provide more information on the probability of default.

To compute DLI, Vassalou and Xing (2004) use three economically sensible inputs: V_A/X, μ, and σ_A. Empirically, μ, computed as the mean of changes in $\ln V_A$, is closely related to stock returns (ret). V_A/X is closely related to financial leverage ($lev = D/E$), as $V_A/X \simeq 1 + 1/lev$. Finally, σ_A measures the volatility of the assets over the return estimation horizon, which cannot be directly observed but must be estimated using the return and firm asset value; σ_A, then, is also closely related to the stock return volatility. DLI can be thought of as an all-in-one measure, defined as a nonlinear transformation of leverage with two additional variables, i.e., $DLI = f(lev,\ ret,\ \sigma_A)$. In a unreported variance decomposition exercise, we find that the past stock return is an important

determinant of DLI, especially among stocks in the top DLI decile.[1] This should not surprise us as DLI is estimated directly using current stock price. In the next section, we examine in details the role of past return in driving Vassalou and Xing's findings.

III. Default Risk or Short-term Return Reversal?

We sort all stocks into deciles according to their default likelihood indicators (DLI) at the end of every month over 1971-1999. We then compute equal-weighted average stock returns after portfolio formation. Since DLI is directly related to actual default and delisting from major exchanges, delisting returns are carefully handled in our empirical exercise using CRSP delisting returns.

The results are provided in Table 1. Stocks in the highest DLI decile (decile 10) earn 2.10% in the first month, a much higher return than for the other deciles. In particular, the large return difference between high-DLI and low-DLI stocks of about 97 bps in the first month is similar to the return difference documented by Vassalou and Xing (2004). However, the large return difference is driven primarily by stocks in the highest DLI decile. There does not seem to be a monotonic relation between DLI and first-month portfolio returns for stocks in DLI deciles 1 to 9.

Insert TABLE 1 about here

Table 1 also documents other characteristics of the ten DLI-sorted portfolios. As in Vassalou and Xing (2004), the highest DLI stocks are associated with the smallest size and highest book-to-market ratios. The highest DLI stocks are clearly past losers. They lost 51.96% in the last year and 3.39% in the last month. Not surprisingly, high DLI stocks also trade at low prices. In fact, the average price declines monotonically with DLI. The highest DLI stocks trade at a mean of \$3.58. The low trading price makes the percentage transaction cost much higher for financially distressed stocks, thus making them more illiquid at the same time.

Amihud (2002) proposes an "illiquidity" measure as follows:

[1] The variance decomposition exercise relates DLI to past return, leverage and asset volatility. Specifically, we show that the variation in past one-year return across high DLI stocks accounts for more than 70% of the variation in DLI. Detailed results are available upon request.

$$Amihud_t = \frac{1}{T}\sum_{d=1}^{T}\frac{|R_{i,t-d}|}{Vol_{i,t-d}} \tag{2}$$

We average the daily absolute value of the ratio between return and dollar trading volume of individual stocks during the portfolio formation month to compute the Amihud measure. The fourth from the last column of Table 1 shows that Amihud's illiquidity measures increase almost monotonically with DLI.

In the third from the last column, Table 1 reports the average idiosyncratic risk measures for stocks by decile. For each month and each stock, we regress the daily stock excess returns on the Fama-French three factors over the past six months, and take the $1 - R^2$ (where R^2 is the adjusted-R^2) as a measure of firm-level idiosyncratic risk. The idiosyncratic risk measure increases monotonically with DLI. For stocks with the highest DLI, nearly 97% of the total risk is idiosyncratic. 74% of stocks in the lowest DLI decile receive analyst coverage; 5.4 analysts on average follow each stock, if the stock receives analyst coverage at all. Only 20% of stocks in the highest DLI decile receive analyst coverage, and in this case, there are only 2.5 analysts per stock, if the stock receives analyst coverage at all.

In summary, the highest DLI stocks are characterized by small market capitalization, high book-to-market ratios, low trading prices, low levels of liquidity, high idiosyncratic risk and little Wall Street coverage.

A. First Month vs. Second Month

If the high return on stock in the highest DLI decile during the first month is explained by exposure to systematic default risk, we would expect the return to persist for some time. This is not the case, as we see in Panel A of Table 2.

Insert TABLE 2 about here

The return of the high DLI portfolio (including stocks in the highest DLI decile) immediately drops by more than a quarter, from 2.10% in the first month to 1.52% in the second month after

portfolio formation. This drop of 58 bps is highly significant (with a t-value above 10). A low DLI stock portfolio, which includes stocks in DLI deciles 1 to 5, on the other hand, earns slightly more during the second month than the first month (1.37% compared to 1.28%). The return difference between the high DLI portfolio and the low DLI portfolio is positive and significant only during the first month but not in the second. Once we skip the first month and look at long-run portfolio returns in months 2-6 and months 2-12 after portfolio formation, the stocks in the highest DLI decile now earn lower returns than those in the low DLI portfolios, consistent with findings in the recent literature. The high-low return spreads after the first month are both negative and significant.

Panel B of Table 2 reports the Fama-French three-factor risk-adjusted returns and factor loadings. For the high DLI portfolio, a simple time series regression of its first-month return on the Fama-French three factors yields a significant positive alpha of 64 bps. This finding is consistent with the asset pricing test results in Vassalou and Xing (2004), and seems to indicate that the return on high default risk stocks is too high to be explained by the standard Fama-French three factors.

If we use the second-month return instead, the alpha drops to 3 bps. The decline in the alpha (from 64 to 3 bps) is very close to the 58 bp drop in average return from the first to the second month. The drop in alpha is not likely driven by change in risk exposure as captured by the three factor loadings, which barely change. As a comparison, the factor risk-adjusted returns on the low DLI portfolio are insignificant, whether we use the first-month or the second-month return. As a result, the high-low return spread, after factor risk adjustment, is significant only during the first month.

To account for the possibility that risk associated with high DLI stocks might be nonlinear and thus not fully captured by a linear factor model, we also compute the characteristics-adjusted return as in Daniel, Grinblatt, Titman, and Wermers (1997). The results are reported in Panel C of Table 2. For each stock in the highest DLI decile, we compute excess return over the return on a benchmark portfolio constructed by matching on size, book-to-market, and momentum characteristics. These excess returns are then equally weighted to form the portfolio characteristics-adjusted return.

Once again, for the high DLI stock portfolio, the first-month characteristics-adjusted return is positive and significant (0.69% with a t-value of 4.08), but the second-month characteristics-

adjusted return is much lower and insignificant (0.04% with a t-value of 0.24). The drop of 65 bps resembles what we find for the three-factor model. The characteristics-adjusted returns on the low DLI portfolio, however, are insignificant whether we use the first-month or the second-month return. Even with characteristics adjustment, the high-low return spread is significant only during the first month.

As the risk characteristics of a stock do not change significantly over a month (see Panel C of Table 2), the second-month returns can be used in asset pricing tests. We conduct cross-sectional asset pricing tests in a Generalized Method of Moments (GMM) framework. Denoting the factors as F and the stochastic discount factor as $m = a + bF$, we want to test:

$$E[mR] = 1$$

where R denotes the equal-weighted return vector of the test portfolios. The GMM is estimated using the optimal weighting matrix. The GMM test results are provided in Panel D of Table 2.

Consistent with the results in Vassalou and Xing (2004), for the ten DLI-sorted portfolios and the first-month returns, an aggregate default risk factor, dSV, computed as the changes in the average DLI across all stocks, is significant even with the presence of the Fama-French three factors. The significance of dSV disappears in second-month returns. Similar results are obtained when we repeat the GMM tests on the 27 portfolios formed by independent triple sorts on DLI, size and book-to-market ratios as in Vassalou and Xing (2004); dSV becomes insignificant once we use second-month returns even though the risk characteristics of the stock do not change significantly after one month for the 27 portfolios.

Overall, we show that the positive default risk premium in Vassalou and Xing (2004) is driven by the positive abnormal return on the highest default likelihood indicator (DLI) stock portfolio during the first-month after portfolio formation. While portfolio characteristics and factor loadings barely change, the positive abnormal returns occur only during the first month and disappear afterwards. If we skip the first month and use the second-month portfolio returns in pricing tests, the aggregate default risk factor becomes insignificant. We conclude that, given its temporary nature, the abnormal return on the highest DLI stock portfolio during the first month after portfolio formation is unlikely to be compensation for the systematic default risk.

B. *DLI* vs. Past Returns

High *DLI* stocks are recent losers. Which factor then explains their abnormal first-month return: *DLI*, or past one-month return? To address this question, we first use a double-sort. Every month, we first sort the stocks in the top *DLI* decile into quintiles on *DLI*s. Within each quintile, we further sort stocks into five portfolios on past one-month returns. This sequential double-sort results in 25 portfolios. The average *DLI*s and returns are provided in Table 3.

Insert TABLE 3 about here

Recent losers among high *DLI* stocks (the bolded column in Table 3) earn much higher return than recent winners during the first month after portfolio formation (6.04% vs. −1.26% on average in Panel D) although they have similar *DLI*s by construction. Their high returns during the first month (6.04%) drive the abnormal first-month return on the high *DLI* stock portfolio. The other high *DLI* stock portfolio does not earn abnormal returns during the first month. This finding indicates that the abnormal first-month returns on high *DLI* stocks are likely driven by the short-term return reversal on high *DLI* losers. Since book leverage and the asset volatility of a firm do not change drastically at monthly intervals, a large negative stock return on high *DLI* losers will lead to a higher *DLI* measure. This is evident when we compare Panels A to B in Table 3. High *DLI* losers experience a sharp increase in their average *DLI* recently (from 24.2% to 37.3%).

Sorting stocks into portfolios according to one characteristic will inevitably induce dispersion along the dimensions of other characteristics. To control for these characteristics simultaneously, we therefore use a cross-sectional regression approach at the individual stock level. If the first-month high returns on high *DLI* stocks are in fact driven by high default risk, and *DLI* captures default risk better than other stock characteristics, we would expect *DLI* to be significant in the cross-sectional regression even in the presence of other stock characteristics. Conversely, if the first-month high return is a result of the short-term return reversal, we would expect past one-month return always to be strongly significant. Finally, as financially distressed stocks are typically illiquid, we would also expect the liquidity measure Amihud to be significant in the regression, among other stock characteristics.

Table 4 presents the results of the cross-sectional regressions. For each month in the 1971-

1999 period, we run a cross-sectional regression of the next-month stock return on various stock characteristics for the current month. All variables are cross-sectionally de-meaned so the intercept term of the regression is zero. Stock characteristics are standardized so that the regression slope coefficient of a variable can be interpreted as the impact on the return of a one-standard deviation change in the variable. The slope coefficients are averaged across time and reported. The robust t-statistic is computed using the Newey-West autocorrelation-adjusted standard error with 12 lags. We consider the variables, *Pastret* (stock return during the month prior to portfolio formation), *Amihud*, *DLI*, *Size* (log of market capitalization), and B/M (book-to-market ratio). We exclude stocks with missing characteristics and negative B/M.

Insert TABLE 4 about here

Panel A of Table 4 reports the regression results for the full sample, with about 1600 stocks in each cross-section. In the first three regressions (Models 1-3), the only regressor is either *DLI*, *Amihud* or *Pastret*. Either *DLI*, *Amihud* or *Pastret* individually is significantly associated with the next-month stock return. *Pastret* is strongly significant (t-value of -9.71) and *Amihud* is slightly more significant than *DLI* (t-value of 4.75 for *Amihud* vs. 3.22 for *DLI*). *DLI*, however, becomes insignificant in the presence of *Pastret* and *Amihud* (Model 4). Model 5 also controls for the *Size* and B/M. Now *DLI* is not significant and assumes the wrong sign, but *Pastret* and *Amihud* are still significant.

Finally, an interaction term between *Pastret* and *Amihud* is negative and significant (Model 6), consistent with the findings in Avramov, Chordia, and Goyal (2006) that short-term return reversal is more pronounced for illiquid stocks. Interestingly, the interactive term subsumes the explanatory power of *Amihud* on a stand-alone basis. Results of the regressions for the group of stocks in the highest *DLI* quintile (with about 270 stocks in each cross-section) are similar (see Panel B of Table 4).

To summarize, we find that the abnormal first-month return on high *DLI* stocks is the manifestation of the short-term return reversal, a well-known stock return pattern (Jegadeesh (1990) and Lehman (1990)). This finding helps to reconcile Vassalou and Xing (2004) findings with the recent literature. Recent authors have adopted empirical procedures that mitigate the effect of such

return reversal. For instance, motivated by our findings, Garlappi, Shu, and Yan (2007) in their empirical exercise skip the first month and focus on second-month returns. Campbell, Hilscher, and Szilagyi (2007) specifically examine annual returns after portfolio formation, which minimizes the impact of the first-month reversal. Finally, in several of their empirical exercises, George and Hwang (2007) exclude the month of January when reversals are the greatest.

IV. Explaining the Short-Term Return Reversal

Having established that the short-term return reversal drives results in Vassalou and Xing (2004), we examine possible causes of short-term return reversal on high-default risk stocks. There are three potential explanations for short-term return reversal: price pressure, bid-ask bounce bias, and investor short-term overreaction. We will examine each in turn.

A. Price Pressure from Institutional Selling

A plausible explanation of the short-term return reversal phenomenon is based on the equilibrium model of Campbell, Grossman, and Wang (1993), where non-information-motivated trades will trigger a liquidity shock and cause temporary price movements that, when absorbed by liquidity providers, result in a price reversal. Such trades usually lead to higher trading volume. One would also expect such trades to cause greater price reversals for illiquid shocks as their demand curves are more downward-sloping, so trading has a greater price impact. These predictions are supported empirically by Conrad, Hameed, and Niden (1994) and Avramov, Chordia and Goyal (2006).

1. Liquidity Shocks

Since high DLI stocks on average are more illiquid, their greater return reversals could be consistent with a price pressure-based explanation. We provide some supporting evidence in Table 5, where we examine four stock portfolios: (1) low DLI stock portfolio, which includes stocks in DLI-deciles 1-5; (2) high DLI stock portfolio, which includes stocks in the highest DLI decile; (3) high DLI loser portfolio, which includes 20% of high DLI stocks with relatively low past one-month returns after controlling for DLI; (4) other high DLI stock portfolio, which includes the remaining 80% of high DLI stocks that are not in the high DLI loser portfolio.

Insert TABLE 5 about here

For each portfolio, we tabulate in Panel A the average liquidity-related portfolio characteristics two months and one month prior to portfolio formation, the difference and the t-value associated with the difference. These liquidity characteristics include: *Turnover* (monthly trading volume divided by total number of shares outstanding); *Amihud*; *Oimb* (an order imbalance measure, defined as the number of buyer-initiated shares purchased less the number of seller-initiated shares sold, scaled by the total number of shares outstanding); *PQspread* (the percentage quoted spread, defined as the ratio between the quoted bid-ask spread and the midpoint of the quoted bid and ask); *PEspread* (the percentage effective spread, defined as $2|P - mid|/mid$); and *PRspread* (the percentage realized spread). *PEspread* allows for the possibility that a trade could take place within the bid-ask spread, which explains why it is smaller in size. *PRspread* measure the reward to market makers for providing liquidity. A detailed estimation procedure is described in Huang and Stoll (1996). The time horizon used for the estimation is 30 minutes. The order imbalance measure and the spread-based measures are computed using intraday quote data from TAQ (after 1993) and from ISSM (before 1993). The sampling period for NYSE/AMEX stocks is 1983-1999, and the sampling period for NASDAQ stocks is 1987-1999.

The *Turnover* measure shows that the high *DLI* loser portfolio, which drives most of the abnormal returns on the high *DLI* stocks, is indeed associated with more trading activities than the low *DLI* portfolio. In the month prior to portfolio formation, when high *DLI* losers experience a -27% return, the turnover increases significantly by 0.57% with a t-value of 2.81. The *Amihud* measure indicates that high *DLI* losers are more illiquid than the other stocks. High *DLI* losers also become more illiquid during the month prior to portfolio formation. The same pattern is observed when illiquidity is measured as a wider *PQspread*, *PEspread* or *PRspread*.

When we look at the order imbalance measure, we confirm selling pressure on high *DLI* losers during the month prior to portfolio formation. *Oimb* changes from 0.09% to -3.57%; the change of -3.67% is highly significant, with a t-value of -6.64, indicating that trades are initiated mostly by sellers. In contrast, there is little change in average liquidity-related characteristics for the low *DLI* stock portfolio and the other high *DLI* stock portfolio.

2. Clientele Changes

The changes in liquidity-related characteristics point to a liquidity shock on the trading of high DLI stocks and in particular high DLI losers during the month prior to portfolio formation. The empirical challenge is to identify the cause of such a phenomenon. We provide empirical evidence supporting the view that such a liquidity shock is a result of a clientele change, which is in turn triggered by institutional selling of high DLI stocks and high DLI losers in particular.

Institutional investors are often required to invest in stocks that are liquid, with considerable market capitalization and stable dividend payouts (see Almazan, Brown, Carlson, and Chapman (2004)). A high DLI loser is less likely to satisfy these requirements when its default likelihood increases (see Table 1), which will trigger selling among the institutional investors who hold such a stock. When a sudden change in the clientele for a stock triggers selling by one group of investors, with no simultaneous compensatory increase in the demand from ready buyers, the imbalance results in a liquidity shock.

To pursue this view, we first document that institutional investors significantly reduce their holdings of high DLI losers. We first examine mutual funds because they constitute a relatively homogeneous group of investors required to issue regular disclosures by the Securities and Exchange Commission (SEC). There is anecdotal evidence that a typical mutual fund tends to avoid low-priced distressed stocks so as not to be seen as speculating or imprudent. An eventual delisting would be costly to stockholders, and SEC rules preclude most institutions from holding unlisted shares (see Macey, O'Hara, and Pompilio (2004)). Liquidity evaporates when delisted stocks are later traded on the OTC Bulletin Board or the Pink Sheets (see Harris, Panchapagesan, and Werner (2004)). For these reasons, mutual funds may want to sell stocks even before an eventual delisting. Finally, mutual funds may "window-dress," or sell recent losers before reporting their holdings (see Haugen and Lakonishok (1988)). This could be another reason why an increase in financial distress could trigger a clientele change and selling by mutual funds.

The mutual fund holding data come from the CDA/Spectrum mutual fund holding database, which collects holding information from N30-D filings to the SEC. Since small holdings are exempt from reporting by SEC regulations, mutual fund holdings may be truncated at the lower end.[2] It

[2] For example, N30-D form filing guideline states "a Manager may omit holdings otherwise reportable if the Manager holds, on the period end date, fewer than 10,000 shares and less than $\$200,000$ aggregate fair market

is thus likely the number of mutual fund shareholders is understated according to CDA/Spectrum, but the impact should be relatively small. To assess the bias, we further sort the stocks into three groups based on the breadth of ownership and obtain similar results across the three groups. We report in Panel B of Table 5 statistics from the full sample (1980-1999) and two subsamples (1980-1989 and 1990-1999) to ensure that the results are not driven by the later period, when there is a dramatic increase in the number of mutual funds.

We infer mutual fund buy and sell decisions by looking at aggregate mutual fund holdings and holding changes when stocks become financially distressed. Specifically, at the end of each month t, for each stock i and fund j in the sample, we identify the most recent fund holding prior to that month ($H_{i,j,t-}$) and the fund holding at that month-end or right after that month ($H_{i,j,t+}$).[3] These holdings are first scaled by the total number of shares outstanding and then aggregated across mutual funds to derive the aggregate mutual fund holdings for each stock. Finally, the aggregate holdings are averaged across stocks and time.

Our conjecture about clientele change holds for mutual funds as a group. For the full sampling period from 1980 through 1999, while mutual funds increase their holdings of low DLI stocks, they significantly reduce their holdings of high DLI stocks, particularly, high DLI losers. The average quarterly holding change on the high DLI loser portfolio is -0.75%, higher than the change on the other high DLI stock portfolio (-0.39%); the difference of -0.36% is highly significant. Similar patterns are documented in both subsample periods.

In Panel C of Table 5, we document a similar clientele change using the CDA/Spectrum Institutional 13F Stock Holdings and Transactions database, which reports quarterly transactions and holdings by institutional investors. As in the case of mutual funds, we infer institutional trading activities by looking at aggregate quarterly institutional holding changes when stocks become financially distressed. We then report the average holding changes from 1980 through 1999 across five types of institutions including banks, insurance companies, investment companies, investment advisors and other institutions. Most institutions (except those in the others category) significantly reduce their holdings of high DLI stocks but not the low DLI stocks. In addition, the institutional selling pressure is much heavier on high DLI losers than on other high DLI stocks. The total

value."

[3] In most cases, $H_{i,j,t-}$ and $H_{i,j,t+}$ are one quarter apart. For a small portion of mutual funds that report holdings on a semi-annual basis, they are six months apart.

quarterly holding change across all institutions on the high DLI loser portfolio is -3.58%, much higher than the change on the other high DLI stock portfolio (-2.20%). The difference is highly significant for most institutions except insurance companies as a group. In conclusion, although some institutions are buying high DLI stocks, all the institutions as a group are selling high DLI stocks and high DLI losers in particular. This clientele change is consistent with recent findings on individual and institutional trading behavior. For instance, Kaniel, Saar, and Titman (2008) show that individual tend to buy NYSE stocks (inferring institutional selling) following declines in the previous month.

One potential problem in using quarterly stock holdings by mutual funds and other institutions is that we cannot rule out the possibility that mutual fund holding changes actually occur during the month prior to or the month after the change in DLI. Ideally, one would like to examine institutional trading activities in the same month a stock experiences a sharp increase in DLI. This becomes possible with the help of a proprietary institutional trading dataset provided by the Plexus Group, a consulting firm for institutional investors that monitors the cost of institutional trading.

Plexus Group customers consist of over 200 financial institutions that collectively transacted over $4.5 trillion in equity trading prior to its acquisition by ITG, Inc. By early 2003, Plexus Group had analyzed 25% of exchange-traded volume worldwide. Researchers using Plexus Group data include Keim and Madhavan (1995) and Conrad, Johnson, and Wahal (2003). The Plexus Group dataset we use covers 1991Q2-1993Q1and 1996Q1-1998Q1.

The dataset records the details (date, size, buy/sell indicator, type of order) of every institutional order for all the institutions Plexus Group monitors. It also records when and how many orders actually are executed. Therefore, for every stock in our sample during the month prior to portfolio formation we are able to compute the aggregate net buy/sell orders (as a percentage of the total number of shares outstanding) submitted by institutions and the actual aggregate shares bought/sold (again as a percentage of the total number of shares outstanding) by institutions at monthly frequency. We can then average these two institutional trading measures first across all stocks at the portfolio level and then across time. Although this yields a refined and precise measurement of institutional trading, the trade-off is a short sampling period and results for only a subset of the universe of all institutions.

The monthly institutional trading results in Panel D of Table 5 confirm the significant selling pressure on high DLI stocks and high DLI losers in particular. While institutions monitored by Plexus (as a group) bought low DLI stocks, they submitted significantly more sell orders and, on average, sold high DLI stocks. In the sample of high DLI stocks, they submitted significantly more sell orders and sold significantly more high DLI losers than other high DLI stocks.

Because there is much less Plexus Group coverage in the first subsample (1991Q2-1993Q1), the institutional trading measures could be quite noisy, especially for high DLI losers. For this reason, Panel D reports results for both the full sample and a later subsample. While the conclusions are similar in both samples, the institutional selling pressure on the high DLI loser portfolio is indeed more significant when we exclude the earlier periods.

The selling of financially distressed stocks by institutional investors such as mutual funds is unlikely to be absorbed by ready outside buyers, as it takes time and human capital for an investor to identify a profitable opportunity and then act on it (see Berndt, Douglas, Duffie, Ferguson, and Schranzk (2005)). We believe such "capital immobility" to be especially relevant for the trading of financially distressed stocks. The results of distressed securities investing depend on an investor's efficiency in uncovering and analyzing all the variables specific to the distressed company. The investor: "will not only know everything about the company and its financials but will have studied the creditors involved in the reorganization as well: their numbers, their willingness to compromise, and the complexity of their claims help indicate how long the reorganization will last, what the asset distributions will be, and whether the expected returns are worth the wait (see Friedland (2005))." Gathering and analyzing such firm-specific information is a daunting task and very time-consuming. The absence of Wall Street research coverage on distressed firms makes the job even harder. When there is heavy selling pressure and a lack of immediate ready buyers, the liquidity shock can be persistent, and the price concession can last for a few days or even up to a month for financially distressed stocks.

B. Bid-ask Bounce Bias

By construction, firms that are facing financial distress or considerable default risk are typically associated with small market capitalization and low trading prices. The average market value and trading price of high DLI stocks are \$39.6 million and \$3.58, respectively. One particular problem

associated with stocks traded at low prices is that the random bid-ask bounce could lead to a non-negligible upward bias in average return computation, as discussed in Blume and Stambaugh (1983) and more recently in Bessembinder and Kalcheva (2007). In fact, bid-ask bounce is often one of the reasons researchers skip a week or a month between portfolio formation and the portfolio holding period in return momentum studies. Mech (1993) discusses several ways of controlling for bid-ask bounce in portfolio return calculation. A natural question is whether the first-month high return on the highest DLI stock portfolio is entirely driven by bias due to such a bid-ask bounce. To address this question, we first estimate the impact of the bid-ask bounce on return. Blume and Stambaugh (1983) show that the bias on return per period due to the bid-ask bounce can be measured by $\left(\frac{P_A - P_B}{P_A + P_B}\right)^2$, where P_A and P_B are the bid and the ask price. The bid-ask bounce bias measure is computed in a subsample for 1983-1999, using the actual quoted spread (quoted ask – quoted bid) from quote data in TAQ and ISSM. As trades could occur between the quoted bid and quoted ask, this bias measure is likely to be overstated and will serve as an upper bound of the true bias from bid-ask bounce.

In a more direct way of accounting for the bid-ask bounce, we also compute the monthly return using daily returns from the second positive trading-volume day. This resulting return measure is therefore largely free from the bid-ask-bounce bias and can be estimated for the entire sampling period, 1971-1999.

The results are provided in Table 6. For the high DLI stock portfolio, the bias measure is 40 bps, which is lower than the abnormal return of above 60 bps (see Table 2). We also report the results on quintiles of high DLI stocks sorted on market capitalization. Since the average trading price declines with the market capitalization, the bias measure not surprisingly rises for the smaller stocks. The spreads between the bias measures are, however, uniformly smaller than the spreads between average first-month returns, indicating that the first-month high returns are not entirely driven by a random bid-ask bounce.

Insert TABLE 6 about here

When we exclude the return on the first trading day of the calendar month, the return drops only slightly. For example, the first-month return of the high DLI stocks drops from 2.10% to 2.01%,

indicating that the true impact of bid-ask bounce is small. Although the drop in the first-month return is much higher for the smallest high DLI stocks (from 6.47% to 5.87%), the first-month return excluding the first trading day of 5.87% is still too high to be explained by most risk models. All this evidence seems to suggest that random bounce between bid and ask does not fully explain the first-month high return on the high DLI stock portfolio.[4]

C. Investor Overreaction

The short-term return reversal we have documented for high DLI stocks is also potentially consistent with investor overreaction, as explored in various behavioral models such as De Long, Shleifer, Summers, and Waldmann (1990), Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998).

Although we cannot completely rule out such explanations based on investor overreaction, we think that they are less compelling than the price pressure-based explanation. First, the close tie between the price reversal on high DLI stocks and the changes on their liquidity-related characteristics we document is more consistent with a price pressure story.

Second, Hirshleifer (2001) suggest that behavioral biases such as overconfidence should be stronger when the decision environment is more uncertain and feedback is slow. Under the overreaction-based explanation, one typically would expect greater reversal for a stock associated with higher uncertainty. When we look at high DLI losers and apply a cash flow-based uncertainty measure developed by Zhang (2006). At the end of each month, we sort high DLI losers into two portfolios according to the uncertainty measures and compute the equal-weighted portfolio return during the first month after portfolio formation for each portfolio separately. The first-month returns on the two portfolios are similar: 6.87% for high DLI losers with high uncertainty measures and 7.04% for high DLI losers with low uncertainty measures. The difference of 17 bps is not significant (t-value = 0.29). We therefore reject increased uncertainty or related investor overreaction as the primary explanation of the first-month high return on the high DLI stock portfolio.

[4] It is possible that prices of high DLI stocks, bounce systematically from bid at the end of portfolio formation month to ask at the end of the first month after. This systematic bid-ask bounce would produce a much higher first-month return on these stocks, but such a systematic bid-ask bounce is entirely consistent with our price pressure-based explanation. The fact that trading occurs at the bid during portfolio formation indicates high selling pressure after the stock becomes financially distressed. As more buyers come to the market in the next month, trade occurs at the ask.

V. Conclusion

Vassalou and Xing (2004) show that stocks of firms experiencing financial distress (measured using the default likelihood indicator or DLI) earn a high positive abnormal return even after adjusting for risk using standard asset pricing models. This finding poses a puzzle for the literature on financial distress or default risk, as most research documents the opposite relation. We resolve this puzzle by first showing that the abnormal return on high-default risk stocks documented by Vassalou and Xing (2004) occurs only in the first month after portfolio formation and is concentrated in a small subset of high-default risk stocks that recently experienced a large negative return (high DLI losers). When second-month returns after portfolio formation are used in various asset pricing tests, the default risk premium disappears, and an aggregate default risk factor is no longer significant. Overall, there is no evidence that the abnormal high return during the first month is compensation for bearing a systematic default risk. Instead, the importance of the last month's returns indicates that this is a manifestation of the well-known short-term return reversal documented by Jegadeesh (1990) and Lehman (1990).

We examine several possible causes of such short-term return reversal for high DLI stocks and high DLI losers in particular. We find that the short-term return reversal is likely a result of a liquidity shock created by the trading of non-information- motivated traders. Empirically, the changes in a variety of liquidity-related characteristics all point to such a liquidity shock on the trading of high DLI stocks and high DLI losers in particular during the month prior to portfolio formation.

We provide evidence supporting the view that a clientele change following a sharp increase in default risk triggers such a liquidity shock. As a firm becomes more financially distressed, financial institutions currently holding its stock have to sell because of various investment restrictions. We document significant institutional selling of such stocks by close examinations of quarterly mutual fund holding changes and a proprietary institutional trading dataset.

By reconciling Vassalou and Xing (2004) with the recent literature on default risk, we present a convincing case that persistent liquidity shocks can have a severe impact on empirical asset pricing tests. Liquidity shocks are particularly relevant for financially distressed stocks, and must be accounted for in the empirical examination of default or financial distress risk.

After accounting for the impact of short-term liquidity shock on distressed stocks, much of the recent evidence suggests that default or financially distressed risk could lead to a lower stock return. This finding presents a new puzzle as financially distressed stocks are more risky according to standard risk measures such as return standard deviation, market beta and loadings on value and small-cap risk factors (see Campbell, Hilscher, and Szilagyi (2007)). In addition, the relation between default risk and stock return also depends on other factors such as book-to-market ratio (see Griffin and Lemmon (2002)) and shareholder advantage (see Garlappi, Shu, and Yan (2007)). Our findings suggest that the examination of the clientele change and related trading on the financially distressed security may aid in answering questions related to the timing of distress returns.

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TABLE 1: Characteristics of 10 *DLI*-sorted Portfolios

At the end of each month over 1971-1999, we sort all stocks into ten deciles according to *DLI* (decile 1: Low *DLI* and decile 10: High *DLI*). We report the equal-weighted characteristics of these portfolios. The Amihud illiquidity measures are multiplied by 1000. The average analyst coverage is estimated over 1984-1990.

Port ID	DLI (%)	First-mth return	MktCap (in million)	Book-to-market	Past 1-year return (%)	Past 1-mth return (%)	Price	Amihud	Idio risk	% covered by analysts	# of analyst
1	0.00	0.0113	2164.92	0.62	12.39	2.48	52.12	0.47	86.30%	73.50%	5.39
2	0.00	0.0107	1303.78	0.73	14.49	2.31	29.37	0.92	86.50%	76.70%	4.98
3	0.00	0.0138	926.84	0.75	14.28	2.70	24.48	0.87	88.20%	67.40%	4.55
4	0.01	0.0133	644.64	0.78	14.41	2.68	20.06	1.29	89.00%	62.60%	4.20
5	0.04	0.0138	452.8	0.83	13.80	2.40	17.02	1.56	89.90%	57.00%	3.80
6	0.17	0.014	339.21	0.89	12.21	2.08	14.52	2.51	90.80%	51.70%	3.42
7	0.61	0.0123	225.86	0.99	8.37	1.67	11.51	3.52	91.90%	44.90%	3.11
8	2.15	0.0126	141.27	1.12	0.75	0.86	8.77	6.24	93.30%	36.60%	2.87
9	7.85	0.0118	80.72	1.32	-15.27	-0.22	6.12	11.54	94.80%	29.10%	2.60
10	36.45	0.0210	39.6	1.92	-51.96	-3.39	3.58	31.75	96.60%	20.30%	2.50

TABLE 2: First-month vs. Second-month Returns after Portfolio Formation

This table compares the first and second month returns after portfolio formation for *DLI*-sorted portfolios. Low *DLI* stocks are stocks in *DLI* deciles 1 to 5, and high *DLI* stocks are stocks in the highest *DLI* decile. Panel A reports average returns. Panel B reports three-factor (Fama and French, 1993) risk-adjusted returns and the factor loadings. Panel C reports the characteristics-adjusted returns and average characteristics. The characteristics-adjusted return is computed as the excess return over a benchmark portfolio constructed by matching along size, book-to-market and momentum characteristics. Panel D reports the results of cross-sectional Generalized Method of Moments (GMM) tests. The tests are performed on two sets of portfolio returns: (1) the equal-weighted monthly returns on ten-*DLI* sorted portfolios; (2) the equal-weighted monthly returns on 27 portfolios sorted on size, book to market equity and *DLI*. MKT is the gross returns on the stock market portfolio. dSV is change in the survival rate, or 1 minus the aggregate *DLI*, as in Vassalou and Xing (2004). HML is a zero-investment portfolio, which is long on high BM stocks and short on low BM stocks. SMB is a zero-investment portfolio, which is long on small market capitalization stocks and short on large stocks. The GMM estimations use optimal weighting matrix. J-stat denotes test statistic on the model over-identification restriction. The sampling period is from 1971/01 to 1999/12.

Panel A: Average portfolio returns

	Return (%) mth = 1	Return (%) mth = 2	Return (%) mth = [2, 6]	Return (%) mth = [2, 12]
Low *DLI*	1.28	1.37	6.91	15.09
High *DLI*	2.10	1.52	5.41	13.35
High - Low	0.82	0.14	-1.51	-1.74
t-value	2.39	0.43	-2.08	-2.17

Panel B: Factor-adjusted returns and factor loadings

	3F-adj alpha (%) mth =1		3F-adj alpha (%) mth = 2		Factor loadings mth = 1			Factor loadings mth = 2		
	Mean	t-value	Mean	t-value	MKT	SMB	HML	MKT	SMB	HML
Low *DLI*	0.03	0.61	0.14	1.02	0.90	0.75	0.09	0.89	0.72	0.09
High *DLI*	0.64	2.33	0.03	0.13	1.13	1.85	0.75	1.09	1.79	0.75
High - Low	0.62	2.27	-0.11	-0.41	0.23	1.10	0.66	0.20	1.07	0.65

Panel C: Characteristics-adjusted returns and portfolio characteristics

	Char-adj return (%), mth =1		Char-adj return (%), mth = 2		Characteristics at formation			Characteristics one month after formation		
	Mean	t-value	Mean	t-value	DLI (%)	MktCap (in million)	Book-to-market	DLI (%)	MktCap (in million)	Book-to-market
Low *DLI*	-0.02	-0.59	0.04	0.92	0.1	1283.6	0.72	0.1	1301.9	0.73
High *DLI*	0.69	4.08	0.04	0.24	36.4	41.0	1.92	34.9	42.1	1.89
High - Low	0.72	3.64	0.00	0.01	36.3	-1242.5	1.19	34.8	-1259.8	1.16

Panel D: Cross-sectional GMM test results

	10-DLI sorted portfolios											
	First-month returns						Second-month returns					
	constant	MKT	SMB	HML	dSV	J-stat	constant	MKT	SMB	HML	dSV	J-stat
coeff.	0.85	13.43	-17.02	24.75		49.77	0.88	8.77	-11.47	19.15		14.76
t-value	10.31	1.72	-2.38	2.38		0.00	14.69	1.65	-2.18	2.34		0.02
coeff.	0.81	12.00	21.17	38.43	-132.17	8.38	0.84	12.44	-6.5	25.18	-33.12	7.63
t-value	6.79	1.28	1.56	2.9	-3.08	0.14	10.26	1.77	-0.86	2.36	-1.11	0.18

	27 size / BM /DLI sorted portfolios											
	First-month returns						Second-month returns					
	constant	MKT	SMB	HML	dSV	J-stat	constant	MKT	SMB	HML	dSV	J-stat
coeff.	1.00	0.82	0.53	-5.13		163.05	0.98	1.77	-1.32	-3.42		113.12
t-value	44.31	0.41	0.23	-1.86		0.00	46.22	0.85	-0.58	-1.23		0.00
coeff.	0.93	4.88	7.85	-5.21	-39.44	133.69	0.95	4.55	3.29	-2.02	-25.98	111.37
t-value	28.95	1.76	1.89	-1.68	-2.15	0.00	27.99	1.35	0.74	-0.62	-1.17	0.00

TABLE 3: *DLI* / Past One-month Return Sort within High *DLI* Decile

At the end of each month over 1971-1999, we sort stocks in the highest *DLI* decile into 25 portfolios using a 5 by 5 sequential double-sort (*DLI* first, past one-month return second). For each portfolio, we report the average *DLI* one-month prior to and at portfolio formation. We also report the portfolio return one month prior to (mth = -1) and one month after (mth = 1) portfolio formation. The columns that correspond to stocks with the lowest past one-month returns (after controlling for *DLI*) are shaded. These stocks are the high *DLI* losers.

	Recent Winner	2	3	4	Recent Loser	Average	Recent Winner	2	3	4	Recent Loser	Average
	Panel A: *DLI* 1-mth prior to formation (%)						Panel B: *DLI* at formation (%)					
High *DLI*	73.0	66.8	62.0	58.5	**52.9**	62.7	67.6	67.8	67.2	68.2	**72.1**	68.6
2	53.2	44.7	40.1	35.6	**27.8**	40.3	43.8	43.8	43.9	43.9	**44.3**	44.0
3	40.4	32.0	27.8	24.1	**18.3**	28.5	30.8	30.7	30.7	30.9	**31.0**	30.8
4	31.4	24.0	20.3	17.4	**12.8**	21.2	22.4	22.3	22.4	22.4	**22.5**	22.4
Low *DLI*	24.9	18.5	15.4	12.9	**9.3**	16.2	16.7	16.6	16.7	16.7	**16.7**	16.7
Average	44.6	37.2	33.1	29.7	**24.2**		36.3	36.2	36.2	36.4	**37.3**	
	Panel C: Return (%), mth = -1						Panel D: Return (%), mth =1					
High *DLI*	24.32	0.16	-9.45	-19.12	**-36.78**	-8.2	-1.12	1.23	1.73	4.57	**10.10**	3.3
2	26.66	3.08	-5.66	-13.67	**-27.23**	-3.4	-1.43	1.02	1.47	3.58	**6.75**	2.3
3	26.05	3.68	-4.35	-11.69	**-24.61**	-2.2	-1.40	2.44	1.36	2.37	**4.93**	1.9
4	25.90	4.01	-3.78	-10.73	**-22.72**	-1.5	-1.20	0.38	1.44	2.53	**4.16**	1.5
Low *DLI*	25.47	4.08	-3.38	-10.08	**-21.79**	-1.1	-1.17	0.39	1.31	2.13	**4.24**	1.4
Average	25.68	3.00	-5.32	-13.06	**-26.63**		-1.26	1.09	1.46	3.04	**6.04**	

TABLE 4: Cross-sectional Regressions with Stock Characteristics (1971-1999)

We run monthly cross-sectional regressions of the next month stock returns on various current month stock characteristics. All variables are cross-sectionally de-meaned so the intercept term is zero. The stock characteristics are also standardized so the regression slope coefficient can be interpreted as the impact on the return of a one-standard deviation change in the variable. The slope coefficients are then averaged across time and reported. The robust *t*-value is computed using Newey-West autocorrelation-adjusted standard error with 12 lags. *Amihud* is a liquidity measure; *DLI* is the Default Likelihood Indicator of Vassalou and Xing (2004); *Size* is the log of market capitalization; *B/M* is the book-to-market ratio and *Pastret* is the return one month prior to the portfolio formation. We exclude stocks with missing characteristics and negative B/M. The regressions are estimated for both the full sample (1589 stocks per month on average) and the top *DLI* quintile (272 stocks per month on average). The robust *t*-value is reported below the coefficient estimate in italics.

LHS: first-month return (%)	*Pastret*	*Amihud*	*DLI*	*Size*	*B/M*	*Pastret* Amihud*	R- square
			Panel A: Full sample				
Model 1			0.25				1.07%
			3.22				
Model 2		0.28					0.92%
		4.75					
Model 3	-0.80						0.98%
	-8.78						
Model 4	-0.80	0.23	0.05				2.55%
	-9.18	*4.41*	*0.65*				
Model 5	-0.83	0.19	-0.08	-0.05	0.31		4.26%
	-9.71	*4.11*	*-1.37*	*-0.47*	*3.93*		
Model 6	-0.67	0.05	-0.10	-0.07	0.32	-0.65	4.73%
	-8.60	*0.65*	*-1.67*	*-0.62*	*4.11*	*-8.28*	
			Panel B: High *DLI* quintile				
Model 1			0.62				1.00%
			5.48				
Model 2		0.65					1.24%
		6.08					
Model 3	-2.08						2.10%
	-14.64						
Model 4	-2.07	0.60	0.21				4.16%
	-14.62	*5.59*	*1.93*				
Model 5	-2.04	0.38	-0.11	-0.66	0.62		6.07%
	-14.22	*3.78*	*-1.22*	*-4.62*	*4.81*		
Model 6	-1.75	0.35	-0.14	-0.64	0.64	-0.67	7.03%
	-12.46	*1.79*	*-1.43*	*-4.51*	*5.16*	*-4.17*	

TABLE 5: Institutional Trading and Changes in Liquidity Characteristics

This table reports results on institutional trading and changes in liquidity characteristics on low *DLI* stock portfolio (including stocks in *DLI* deciles 1 to 5), high *DLI* stock portfolio (including stocks in the highest *DLI* decile), high *DLI* losers (including 20% of high *DLI* stocks with relative low past one-month returns after controlling for *DLI)* and other high *DLI* stocks (including high *DLI* stocks that are not high *DLI* losers). Panel A reports the average liquidity characteristics during the second month prior to formation (mth = -2) and the month prior to formation (mth = 1). *Turnover* is defined as monthly trading volume divided by total number of shares outstanding (shrout). *Amihud* is an illiquidity measure. *Oimb* is defined as the number of buyer-initiated shares purchased less than the number of seller-initiated shares sold, scaled by the total number of shares outstanding. *PQspread* measures the average percentage quoted spread defined as (ask – bid) / mid. *PEspread* measures the average percentage effective spread defined as 2|P-mid|/mid. *PRspread* measures the percentage realized spread. Its detailed estimation procedure is described in Huang and Stoll (1996). The time horizon used for the estimation is 30 minutes. The sampling period is 1971-1999. All the spread-based measures are computed using intraday quote data from TAQ (after 1993) and ISSM (before 1993). The sampling period for NYSE/AMEX stocks is from 1983 through 1999 and the sampling period for NASDAQ stocks is from 1987 through 1999.

Panel B reports the aggregate mutual fund holdings before and after the portfolio formation and the implied holding changes. Panel C reports the aggregate institutional holding changes around the portfolio formation across various types of institutions. Panel D reports institutional trading activities using a dataset provided by Plexus Group. For each stock during the month prior to formation, we first compute the aggregate net buy/sell orders (as percentage of total number of shares outstanding) submitted by institutions and actual aggregate shares bought/sold (again as percentage of total number of shares outstanding) by institutions. We then average these two institutional trading measures first across all stocks at portfolio level and then across time. A negative number indicates net selling.

Panel A: Average liquidity characteristics

	mth = -2	mth = -1	change	t-value	mth = -2	mth = -1	change	t-value	mth = -2	mth = -1	change	t-value
	Turnover, volume / shrout				*Amihud*				*Oimb*, (#buy-#Sell)/shrout			
Low *DLI*	0.0566	0.0564	0.0017	0.65	0.0012	0.0013	0.0001	1.35	0.0066	0.0070	0.0005	0.63
High *DLI*	0.0498	0.0500	0.0002	0.20	0.0297	0.0318	0.0021	3.01	-0.0100	-0.0098	0.0000	-0.11
High *DLI* loser	0.0612	0.0669	0.0057	2.81	0.0296	0.0411	0.0115	6.51	0.0009	-0.0357	-0.0367	-6.64
Other high *DLI*	0.0471	0.0459	-0.0012	-1.72	0.0296	0.0295	-0.0002	-0.25	-0.0115	-0.0061	0.0052	1.94
	PQspread				*PEspread*				*PRspread*			
Low *DLI*	0.0203	0.0203	0.0000	-1.76	0.0144	0.0144	0.0000	0.13	0.0002	0.0005	0.0003	-1.10
High *DLI*	0.0987	0.1008	0.0024	4.06	0.0732	0.0748	0.0019	2.79	0.0092	0.0099	0.0007	0.65
High *DLI* loser	0.0982	0.1144	0.0166	15.95	0.0732	0.0844	0.0115	11.38	0.0112	0.0183	0.0073	5.36
Other high *DLI*	0.0989	0.0975	-0.0011	-0.64	0.0732	0.0725	-0.0004	-0.65	0.0086	0.0078	-0.0008	-1.08

Panel B: Aggregate quarterly mutual fund holdings and holding changes

Portfolio	Statistics	MF holding before	MF holding after	Quarterly Holding Changes	MF holding before	MF holding after	Quarterly Holding Changes	MF holding before	MF holding after	Quarterly Holding Changes
		1980 - 1999			1980-1989			1990 - 1999		
Low *DLI*	Mean	6.85%	6.97%	0.11%	4.98%	5.07%	0.10%	8.73%	8.86%	0.12%
	t-value	44.65	45.20	1.21	51.67	64.07	1.77	54.08	51.95	0.70
High *DLI*	Mean	3.94%	3.49%	-0.45%	3.54%	3.17%	-0.38%	4.26%	3.75%	-0.51%
	t-value	61.49	50.75	-6.03	60.48	53.06	-7.14	44.25	34.44	-3.99
High *DLI* loser (1)	Mean	3.91%	3.16%	-0.75%	3.61%	2.79%	-0.82%	4.16%	3.45%	-0.70%
	t-value	41.53	37.67	-8.26	34.00	26.56	-8.62	29.00	29.01	-4.82
Other high *DLI* (2)	Mean	3.94%	3.55%	-0.39%	3.53%	3.23%	-0.30%	4.27%	3.81%	-0.47%
	t-value	61.67	49.46	-5.22	58.05	52.93	-5.50	45.34	33.21	-3.64
(1)-(2)	Mean			-0.36%			-0.51%			-0.24%
	t-value			-5.87			-5.76			-2.86

Panel C: Institutional holding changes by types of institutions

Portfolio	Statistics	Quarterly Institutional Holding Changes					
		Banks	Insurance Companies	Investment Companies	Investment Advisors	Others	All
Low-*DLI*	Mean	0.04%	0.02%	-0.07%	-0.01%	0.89%	0.87%
	t-value	0.34	0.36	-0.43	-0.07	2.95	2.97
High-*DLI*	Mean	-0.34%	-0.43%	-0.78%	-0.91%	0.01%	-2.45%
	t-value	-7.16	-13.76	-6.99	-7.18	0.08	-12.24
High-*DLI* Loser (1)	Mean	-0.50%	-0.51%	-1.14%	-1.29%	-0.18%	-3.58%
	t-value	-12.33	-8.90	-9.86	-9.17	-1.03	-18.93
Other High-*DLI* (2)	Mean	-0.31%	-0.42%	-0.70%	-0.82%	0.04%	-2.20%
	t-value	-6.14	-13.03	-6.34	-6.50	0.21	-11.52
(1)-(2)	Mean	-0.16%	-0.08%	-0.44%	-0.48%	-0.22%	-1.38%
	t-value	-3.47	-1.45	-5.85	-7.22	-2.66	-7.65

Panel D: Monthly institutional trading

Portfolio	net buy/sell order as % of shrout	*t*-value	net shares bought/sold as % of shrout	*t*-value	net buy/sell order as % of shrout	*t*-value	net shares bought/sold as % of shrout	*t*-value
	Full sample (1991Q2-1993Q1, 1996Q1-1998Q1)				Earlier periods excluded (1996Q1-1998Q1)			
Low *DLI*	0.04%	4.42	0.02%	3.82	0.05%	4.28	0.04%	4.31
High *DLI*	-0.18%	-3.50	-0.14%	-3.12	-0.15%	-2.14	-0.15%	-2.05
High *DLI* loser (1)	-0.41%	-2.37	-0.33%	-1.96	-0.26%	-3.02	-0.25%	-2.88
Other high *DLI* (2)	-0.14%	-2.70	-0.11%	-2.34	-0.12%	-1.51	-0.12%	-1.46
(1)-(2)	-0.27%	-2.28	-0.22%	-1.96	-0.14%	-2.40	-0.13%	-2.33

TABLE 6: Impact of Bid-ask Bounce

This table reports the average characteristics of high *DLI* stocks and subsets of high *DLI* stocks after further sorting on market capitalization (MktCap). These characteristics include Mktcap, trading price at formation and return one month prior to (mth = -1) and one month after (mth = 1) the formation, a bid-ask bounce bias measure and first-month return computed using daily returns from the second positive trading volume-day. The bid-ask bounce bias measure is computed as $\left(P_A - P_B\right)^2 / \left(P_A + P_B\right)^2$, where P_A and P_B are the bid and ask price of the stock. The sampling period is 1971-1999. The bid-ask bounce bias measure are computed starting from 1983 due to the availability of TAQ data.

	Mktcap (million $)	Price ($)	Retunr (%) mth = -1	Retunr (%) mth =1	Bid-ask bounce bias	Return (%) mth = 1 w/o 1st day
High-*DLI*	39.6	3.58	-3.39	2.10	0.40	2.02
	High DLI stocks sorted on mktcap					
Large	166.4	8.03	-2.30	0.36	0.08	0.36
2	18.4	4.06	-2.49	0.60	0.24	0.60
3	8.3	2.80	-2.43	0.84	0.40	0.91
4	4.3	1.87	-3.49	2.30	0.54	2.37
Small	1.7	1.18	-6.27	6.47	0.77	5.87