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

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Abstract

This paper provides empirical evidence supporting the view that a sharp rise in a firm's default likelihood causes a change in its shareholder clientele. As institutions decrease their holdings of the firm's share, trading volume and cost increase; the order imbalance measure indicates large selling pressure. The resulting liquidity shock leads to a further concession in the stock price, recovering though, in the subsequent month. Such price recovery explains the first-month abnormal high return earned by stocks with high default likelihood documented in Vassalou and Xing (2004). The abnormal high return is therefore mostly reward for providing liquidity when it is most needed rather than compensation for bearing a systematic default risk.

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In a recent paper, Vassalou and Xing (2004) show that stocks more likely to default earn a higher return than otherwise similar stocks during the first month after they enter the highest default-risk portfolio. Since defaults are more likely to occur in economic downturns, default risk likely contains a nondiversifiable component, thus requiring a risk premium. However, the magnitude of the risk premium appears rather large – the stocks in the highest default risk decile constructed by Vassalou and Xing(2004) earn about 90 basis points more per month than otherwise similar stocks, with an associated monthly Sharpe ratio of around 0.25 during the period from 1970 to 1999. As Hansen and Jagannathan (1991), and MacKinlay (1995) point out, such high Sharpe ratio can not be easily explained within the "perfect and complete markets" paradigm. As a comparison, Fama and French (1992, 1993) conjecture that book-to-market ratio (BM) captures relative distress risk and therefore the average HML return also reflects a premium for relative distress. However, during the same period from 1970 to 1999, the monthly return on HML is only 35 basis points with a monthly Sharpe ratio of 0.13.[1]

In this paper we argue that a sharp rise in a firm's exposure to default risk, as measured by the Default Likelihood Indicator (DLI) as in Vassalou and Xing (2004), triggers a clientele change in its underlying stockholders. It is well recognized in the literature that the downgrading of a bond can cause a change in the underlying clientele for that bond. For example, when the a bond's rating falls below investment grade, some institutions that hold the bonds are required to sell it. We believe that a similar clientele change occurs for the stock of a firm that experiences a sharp rise in the probability of financial distress. Institutional investors are often restricted to invest in stocks that are liquid, with considerable market capitalizations and stable dividend payouts (c.f. Almazan, Brown, Carlson and Chapman, 2004). A stock is less likely to satisfy these requirements when its default likelihood goes up, a phenomenon that will trigger selling amongst institutional investors who currently hold such a stock. Consistent with this view, we find that mutual funds significantly decrease their holdings of stocks from firms that experience a sharp rise in their default likelihood measures. In addition, significant institutional selling of such stocks are also confirmed by a close examination of a proprietary institutional trading dataset.

A sudden change in the clientele for a stock triggers selling by one group of investors with no

[1] These numbers are computed based on the HML factors from Ken French's website.

simultaneous compensatory increase in the demand from ready buyers. This imbalance results in a liquidity shock. In such situations, market makers will have to step in and provide liquidity. A substantial price concession may have to be offered to the market makers for providing immediacy in those situations.[2] The price will bounce back once outside investors recognize the inherent opportunity and move their capital to that stock. However, as Berndt, Douglas, Duffie, Ferguson and Schranzk (2005) point out, the flow of capital to the new investment opportunity will take some time. As expected, the liquidity risk of the stock changes during such liquidity shock. We find that the initial price concession and subsequent price recovery for the stock also coincides with changes in its liquidity risk as measured by its exposure to the Pástor and Stambaugh (2003) liquidity factor. We argue that such price recovery explains a large part of the high return on financially distressed stocks documented in Vassalou and Xing(2004).

The existence of "dividend clienteles" is well documented in the literature.[3] The case of Florida Power and Light Company (FPL) neatly demonstrates the existence of dividend clienteles: a change in its dividend policy causes the clientele holding the stock to sell, resulting in a large temporary price drop.[4,5] Our empirical findings support, additionally, the existence of clientele changes for stocks of financially distressed firms. A sharp rise in the probability of financial distress triggers selling by the clientele holding the stock, resulting in a large price drop followed by a corresponding large positive return when the stock price recovers.

While a stock may experience a sharp change in its exposure to economy-wide, pervasive risk, any such change is likely to persist for a while.[6] In contrast, we find that most of the high returns

[2]This price concession is in addition to the drop in the stock's fundmental value caused by the increase in default risk.

[3]See Allen and Michaely (2002) and the references therein.

[4]We are grateful to S. Viswanathan for bringing this example to our attention. Soter, Brigham and Evanson (1996) present an interesting case study of the sudden dividend cut of FPL, the first ever dividend cut by a healthy utility company with a 46-year history of increasing dividend payout. They suggest that the massive selling by one group of current shareholders induces significant price drop (18% - 20%). This group of shareholders are likely to be "older people who depend heavily on dividends for income and they are largely passive investors concerned mostly with cashing dividend checks." (New York Times, May 12, 1994) Subsequently, "value-based" bargain hunters (large and sophisticated investors) are attracted (institutional ownership increases from 34% at the end of 1993 to 47% at the end of 1995), and price recovered (on May 31, the price of FPL closed 1% higher than the pre-announcement period price).

[5]Brav and Heaton (1998) also document that many institutional investors stop holding stocks that omit dividends in the post-ERISA period when private pension fund managers are subject to a stricter "prudent man" rule.

[6]For example, Jagannathan and Wang (1996) examine changes in systematic risk that takes place at business cycle frequencies.

on stocks that experience sharp increases in their default likelihood measures accrue during the first month following portfolio formation, and little accrue during the months afterwards. Further, various characteristics of those stocks, such as size, book-to-market ratios and default likelihood hardly change from the first- to the second-month since portfolio formation. Such return pattern supports our interpretation that the first-month high return for stocks that experience a large increase in their default likelihood measure should be considered as reward for those who provide liquidity in the market for those stocks when it is most needed. In addition, we also find that:

- These stocks experience significant increases in their trading volumes, trading costs and realized spreads around portfolio formation dates;
- Trading in those stocks are more likely to be seller-initiated during the portfolio formation month when prices are depressed, but are more likely to be buyer-initiated during the month after as prices recover;
- The stock's exposure to the Pastor and Stambaugh (2003) liquidity factor increases significantly during the portfolio formation month, coinciding with the price concession. The exposure then returns to its normal level during the month after, coinciding with the price recovery.
- Past return and its interaction with a liquidity measure (Amihud 2002) drive out DLI in predicting the next-month stock (risk adjusted) returns.

All these observations support our view that a sharp rise in the default likelihood measure of a stock triggers a change in its clientele, which generates a liquidity shock and a temporary price concession, and the subsequent price recovery leads to a higher return on the stock.[7]

Our findings add to the growing literature documenting the significant reward for liquidity provision in equity and bond markets. For example, Keim and Madhavan (1996) find that the

[7] The trading activities of Midway Airlines (ticker = MDW) during July 9 to Aug 10, 1990 plotted in Figure 1 provides a stylized example. Midway Airlines experienced a large increase in its default likelihood during July: the DLI increased from 0.21 at the end of June to 0.49 at the end of July. The increase in DLI was mainly driven by two events: a potential downgrade of the company's preferred stock by S&P announced on July 10 and a large quarterly loss of $11 million dollars announced on July 26. The price of the stock was depressed from $7.875 on July 9 to $6.75 on July 30 accompanied with heavy selling (the order imbalance measures were mostly negative). The price then recovered during Aug as more buyers came into the market (the order imbalance measure became positive). In addition, mutual funds, as a group, decrease their holdings of MDW from 2.4% to 0.6% from June to Sep, indicating a clientele change on its shareholders.

counter party of a block trade will be compensated for providing liquidity. Coval and Stafford (2005) show that investors who trade against mutual funds during equity fire sales earn significant returns for providing liquidity when few others are willing or able. Da and Schaumburg (2005) show that the profit to a trading strategy that exploits the temporary divergence between price and fundamental measured using equity analysts' target prices is likely to contain rewards for liquidity provision. In this paper, we show that out of the 90 bps default risk premium per month documented in Vassalou and Xing (2004), 60 bps are likely to be compensation for liquidity provision. The magnitude of such compensation is in line with those documented in the previous literature.[8]

The temporary liquidity shock and its implication on asset prices have also been analyzed theoretically in the model of Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993), and investigated empirically by Conrad, Hameed and Niden (1994) and, most recently by Avramov, Chordia and Goyal (2005). In this paper, we show that such liquidity shock can also help to explain the first month high return on financially distressed stocks. Of even more interest, we provide supporting evidence that such liquidity shock likely results from clientele change with a stock that has become financially distressed. Here, it is important to draw a conceptual distinction between the *liquidity shock* and the commonly studied *liquidity risk*: the impact of the liquidity shock is usually temporary but the impact of liquidity risk is permanent because it carries a risk premium.[9] The high return on financially distressed stocks is primarily a result of the liquidity shock since it accrues only during the first month after portfolio formation. However, as one would expect, *liquidity shock* and *liquidity risk* are related empirically. We find that a stock does load more on Pastor and Stambaugh's (2003) aggregate liquidity factor during the liquidity shock and the liquidity factor loading (or the liquidity beta) returns to its normal level soon afterwards.

Our findings also contribute to another growing literature that examines the relationship between default risk and stock returns by zooming in on the role of liquidity shock. Whether default

[8] For example, Keim and Madhavan (1996) (50 to 100 bps as in Figure 1 of their paper), Coval and Stafford (2005) (79 bps as in Table 5 of their paper) and Da and Schaumburg (around 100 bps).

[9] Acharya and Pedersen (2005) decompose the *liquidity risk* premium on individual stocks into four parts: (1) the part due to the level of stock liquidity (c.f. Amihud and Mendelson (1986), Amihud (2002)), (2) the part due to the covariance between the stock return and the aggregate liquidity in the economy (c.f. Chordia, Roll, and Subrahmanyam (2001), Pástor and Stambaugh (2003)), (3) the part due to commonality in liquidity among stocks (c.f. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001)), and (4) the part due to the covariance between the level of stock liquidity and the market return.

risk is an economy wide risk factor is one of the fundamental questions in financial economics. Vassalou and Xing (2004) are among the first to analyze the relationship between stock returns and default risk. They isolate stocks with greater default risk exposure and find that these stocks earn higher returns during the first month after portfolio formation – too high to be explained by the Fama-French three factor model (1993), which seems to indicate the need for default risk as an additional risk factor. Recent studies by Campbell, Hilscher and Szilagyi (2005), and Garlappi, Shu and Yan (2005), find, however, that higher default risk does not necessarily lead to a higher stock return. These two seemingly contradictory sets of results could be reconciled by the liquidity shock we have identified for the financially distressed stock. The short-term liquidity-induced price reversal plays a very little role in the latter papers, as Campbell, Hilscher and Szilagyi (2005) specifically examine annual return and Garlappi, Shu and Yan (2005) explicitly exclude very illiquid stocks. Consistent with the results in the latter papers, we show that the impact of default risk on stock returns is significantly reduced if second-month returns are used in various asset pricing tests. Therefore, insisting on the necessity of a separate aggregate default risk factor in reduced form asset pricing models may be premature. As a result, we also reconcile the seemingly contradictory results in Vassalou and Xing (2004) and Fama and French (1996). After accounting for the 60 bps compensation for liquidity provision, the remaining return premium of about 30 bps (90 bps - 60 bps) documented in Vassalou and Xing (2004) can be loosely interpreted as compensation for default risk. Such return premium is comparable to the average HML return in magnitude and can be fully explained by the three-factor model.

Although our initial motivation was to explain the high return earned by financially distressed stocks, our findings will be of interest to a wider audience. First, the fact that there is a clientele change for a stock that experiences a sharp rise in DLI is interesting on its own. Second and more generally, we point out another channel for changes in stock characteristics to affect short-term stock returns: the change in stock characteristic could trigger a clientele change in the stock's shareholders, resulting in a temporary liquidity shock which generates short-run return reversal. Third, we provide an interesting example in which the liquidity beta of a stock changes in a systematic fashion around certain events. Although the change in liquidity beta is perfectly consistent with the price movement around the event, the aggregate liquidity factor may be insignificant in a standard cross sectional asset pricing test using event-window returns. In other words, it is very important to account for the time-varying nature of the liquidity risk. Finally, we highlight the interesting market microstructure dynamics of a stock around the default event. In this respect, our paper is related to recent work by Odders-White and Ready (2005) that shows various market microstructure measures reliably predicting the bond rating changes.[10]

The remainder of the paper is organized as follows: Section 1 briefly reviews various proxies for default and financial distress risk including the Default Likelihood measure (DLI) proposed by Vassalou and Xing (2004). Section 2 shows that financially distressed stocks do not earn significantly higher returns beyond the first month after portfolio formation. Section 3 discusses how leverage, past return and asset volatility collectively contribute to the cross-sectional variation of DLI. Section 3 also provides evidence that a sharp increase in DLI will likely trigger a clientele change and lead to a temporary price concession; that the later price recovery contributes to the high returns on financially distressed stocks during the first month after portfolio formation. Section 4 concludes with a brief summary.

1 Review of Default Likelihood Measures

Previous researchers have identified characteristics that are associated with default or financial distress risk. The most direct measure is financial leverage. A long thread of literature on bankruptcy predictions has consistently found that financial leverage is both economically and statistically significant in predicting the likelihood of bankruptcy, which can be viewed as indirect evidence that financial leverage is related to default risk.[11] Andrade and Kaplan (1998) show that high leverage is the primary cause of distress. Both systematic and idiosyncratic risk increases with financial leverage, *ceteris paribus*, and increases in such risk would be associated with an increase in expected return. Black (1976) points out this "leverage effect" and Bhandari (1988) finds the

[10] Our paper differs from Odders-White and Ready (2005) in three important aspects at least. First, we are interested in how market participants transact when a stock becomes financially distressed. As a result, we identify the economic cause of a liquidity shock. Second, we focus on explaining stock return patterns after a default event while Odders-White and Ready (2005) focus on pre-event stock returns. Third, we examine market implied default likelihood rather than ratings assigned by rating agencies, which gives us a much larger stock sample.

[11] See Shumway (2001) for a more comprehensive survey on this topic.

expected stock returns are indeed positively related to debt-to-equity ratio, even after controlling for beta and size.

B/M is also believed to be associated with default or financial distress risk. According to Fama and French (1992): "A high B/M says that the market judges the prospects of a firm to be poor relative to firms with low B/M. Thus B/M may capture the relative-distress effect." Indeed, Fama and French (1995) show that firms with high B/M have persistently low earnings, higher financial leverage, more earning uncertainty, and are more likely to cut dividends as compared to low B/M firms. Since log B/M can also be expressed as the difference between log market leverage and log book leverage, Fama and French interpret B/M as an "involuntary leverage effect". Since small firms are more prone to default, size is also believed to be associated with distress as in Chan and Chen (1991). Other researchers use only accounting bankruptcy measures for distress risk, for instance, O-score and Z-score in Dichev (1998).[12]

A common criticism against using accounting measures argues that the accounting information can only be updated at a lower frequency. To accommodate this problem, Vassalou and Xing (2004) estimate a default likelihood indicator (DLI) within the Black and Scholes (1973) and Merton's (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 distribution's cumulative density function; 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; 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. Vassalou and Xing (2004) are also among the first to analyze the relationship between default risk and equity return. They find: (1) both size and B/M effect can be viewed as default effects, (2) stocks with high DLI (usually also with small size and high book-to-market ratio) have very high returns during the first month immediately after the portfolio formation. and (3) the change in aggregate DLI (denoted by dSV) is priced in cross-sectional stock returns even with the presence of Fama and French's three factors.

[12] See Ohlson (1980) and Altman (1968) for O-score and Z-score , respectively.

The main advantage to using DLI is that it works from market price information that is updated more frequently than credit rating and other accounting default measures, so it is potentially a better measure for predicting bankruptcy. Vassalou and Xing (2004) show that DLI predicts actual defaults well, and Vassalou and Xing (2005) demonstrate that changes in DLI capture default risk over time better than credit rating upgrading or downgrading. Hillegeist, Keating, Cram and Lundstedt (2004) compare a slightly modified version of DLI against traditional accounting measures: the Z-score and O-score, and find DLI to provide more information on the probability of default than these two accounting measures. Consistent with previous findings, we show that probability of delisting due to performance-related reasons[13] increases monotonically with DLI (see Table I). For stocks in the highest DLI decile, about 12% get delisted due to performance-related reasons during the next one year, compared to only 0.4% for stocks in the lowest DLI decile. For this reason, we decide to use DLI as our default risk measure in this paper.

Insert Table I about here

2 Returns on Financially Distressed Stocks After the First Month

Vassalou and Xing (2004) sort all stocks into 10 deciles according to DLI at the end of each month from 1970 to 1999 and compute equally-weighted portfolio return for each decile during the first month after portfolio formation. They find that the stocks in the highest default risk decile earn about 90 basis points more per month than otherwise similar stocks. If such large return premium on financially distressed stocks during the first month is indeed due to exposure to a systematic default risk, we would expect it to persist for a while provided that the risk characteristics of these stocks hardly change.

Following the portfolio construction in Vassalou and Xing (2004), we sort all stocks[14] into ten deciles according to the DLI measures at the end of every month. We then compute the

[13] CRSP delisting code between 400 and 599.

[14] The leverage ratios of financial firms are usually high due to the nature of their business, which leads to higher DLI measures but do not necessarily reflect high default risk. For this reason, financial firms are often exlcuded as in Garlappi, Shu and Yan (2005). The results in this paper are qualitatively similar if we exclude financial firms as reported in an earlier version of the paper.

equally-weighted average[15] stock returns in each of the first six months after portfolio formation. As the default likelihood is directly related to actual default and delisting from major exchanges, delisting returns deserve careful handling in our empirical exercise. Shumway and Warther (1999) meticulously examine the delisting returns in CRSP and explore their empirical implications with regards to some well-known "anomalies". They suggest assigning -0.30 and -0.55 to performance related delistings of NYSE and NASDAQ stocks, respectively. These two delisting returns are widely used in subsequent literature. Nevertheless, such numbers are slightly outdated, considering the recent completion of a historical project in delisting returns, as shown in CRSP white paper (2001). We take a different approach. If delisting returns are available from CRSP, we use CRSP delisting returns in our calculation. Otherwise, in line with Shumway (1997), and Shumway and Warther (1999), we recompute the average delisting returns based on the nature of delisting, as identified by the CRSP delisting code.[16] The results are provided in Panel A of Table II.

Insert Table II and Figure 2 about here

Two interesting observations stand out. First, the large return difference between high-DLI and low-DLI stocks during the first month is primarily driven by stocks in the highest DLI decile. These stocks earn 2.10% in the first month, much higher than the rest. Second, the return of the highest DLI portfolio immediately decreases by more than a quarter from 2.10% in the first month to 1.52% in the second month, and stabilizes afterwards. This drop of 58 bps is highly significant (with a t-value above 10), and is five times higher in magnitude than the average change in the rest of the portfolio returns. Panel B of Table II reports the average Size, B/M and DLI of the 10 DLI-sorted portfolios one month after portfolio formation. The changes in these characteristics within one month are very small in magnitude. For stocks in the highest DLI decile, these changes are all smaller than 5%. Therefore, the 58 bp drop in return is unlikely explained by changes in risk associated with these stocks. Figure 2 contains graphic representations of this result. The return

[15] We use equally-weighted returns throughout the paper so our results are comparable to those in Vassalou and Xing (2004).

[16] The average of delisting returns based on the nature of delisting are available from the author upon request. As a further robustness check, we rerun our empirical exercises using the delisting return suggested by Shumway and Warther (1999), or simply assigning the delisting return as -1, and the results are quantitatively similar. This is not surprising given the small delisting probability during the first month after portfolio formation (less than 1.5% even for stocks in the highest DLI-decile) as in Table A of Table I.

of the highest DLI stock displays a clear first month reversal pattern, which disappears after the first month.

2.1 Asset pricing tests with the second-month returns

Since the risk characteristics of a stock do not change significantly over a month, the second-month returns might be better choices for asset pricing tests.[17] We show that the impact of aggregate default risk on stock returns is significantly reduced if second-month returns are used.

If we run a simple time-series regression of the first month return of stocks in the highest DLI decile on the Fama-French three factors, we obtain a significant positive alpha of 64 bp. The results are reported below with t-value in bracket. They are consistent with the asset pricing test results in Vassalou and Xing (2004) and seem to indicate that the return of high default risk is too high to be explained by the standard Fama-French three factors. A separate default risk factor seems to be needed in the reduced form asset pricing model.

$$\begin{aligned} R_{HDLI,1} - r_f &= 0.0064 + 1.13MKT + 1.85SMB + 0.75HML \\ & \quad (2.33) \quad (16.64) \quad\quad (18.97) \quad\quad (6.91) \end{aligned}$$

If we use second month return instead, we have:

$$\begin{aligned} R_{HDLI,2} - r_f &= 0.0003 + 1.09MKT + 1.79SMB + 0.75HML \\ & \quad (0.13) \quad (16.48) \quad\quad (19.04) \quad\quad (7.13) \end{aligned}$$

The intercept term drops to a number indistinguishable from zero while the slope coefficients

[17] This is also consistent with standard practice in momentum literature. In addition, it helps to reduce the bias introduced by the bid-ask bounce. In fact, it is often the cited reason for skipping a week or a month between portfolio formation and portfolio holding period in momentum literature. For instance, Jegadeesh and Titman (1993) skip a week to avoid "bid-ask spread, price pressure and lagged reaction effects". Similarly, Fama and French (1996) skip a month to "reduce bias from bid-ask bounce".

hardly change, confirming that risk characteristics of the stock did not change by much during the first month after portfolio formation. The 61 bp decrease in the alpha (from 64 bp to 3 bp) is very close to the 58 bp drop in average return from the first to the second month. This decrease is not likely driven by change in risk as both characteristics and the Fama-French three factor loadings hardly change. Once we use the second month return, the return of high default risk stock can be fully explained by the three factors and we do not need an additional default risk factor.[18]

To confirm this result, we also conduct GMM tests. Denote the factors as F and the stochastic discount factor as $m = a + bF$, we want to test:

$$E[mR] = 1,$$

where R denotes the equally-weighted return vector of the test portfolios. The GMM is estimated using the optimal weighting matrix. The results of the GMM tests are provided in Table III.

Insert Table III about here

We first conduct the GMM tests on the 10 DLI-sorted portfolios (see Panel A). Using 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 . This finding is consistent with the results in Vassalou and Xing (2004), The significance of dSV disappears if the second-month returns are used: dSV ceases to provide any additional explanatory power on top of the three factors. 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 (see Panel B), as in Vassalou and Xing (2004). Again, dSV becomes insignificant once second-month returns are used. We also verify that the risk characteristics of the stock did not change significantly after one month for the 27 portfolios, as in Table IV.

Insert Table IV and V about here

[18] Similar results are obtained for the "new" high DLI stocks which have recently entered the Highest DLI portfolio. The Fama-French three factor alpha is as high as 138 bps (with a t-value of 5.1) if first-month returns are used. The alphas drops to -23 bps (with a t-value of -0.79) if the second-month returns are used.

Table V reports factor loadings on the aggregate default risk factor (dSV) for both 10 DLI-sorted portfolios and 27 portfolios sorted on size, book to market and DLI, during the first and second month after portfolio formation. Overall, the changes in the default risk factor loadings are small. For the highest-DLI stock portfolio, the factor loading decreases from 1.9 to 1.8, but the size of such change is too small to explain the 58 bps drop in return. Again, this seems to indicate that the change in default risk as measured by default factor loading do not explain the decrease in average return from the first to the second month for the highest-DLI stocks.

3 Clientele Change and First-month Returns on Financially Distressed Stocks

3.1 An anatomy of the DLI

To compute DLI, Vassalou and Xing (2004) use three economically sensible inputs: V_A/X, μ and σ_A. Empirically, μ is computed as mean of changes in $\ln V_A$ and is closely related to stock returns (ret).[19] 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.[20] In summary, DLI can be thought of as an "all-in-one" measure, defined as a nonlinear transformation of leverage with two additional variables, i.e., $DLI = f(lev, ret, \sigma_A)$. To better understand DLI, we can look at the relative importance of these three variables. For this purpose, we carry out a variance decomposition exercise similar to those studied in Vuolteenaho (2002). The details are provided in the Appendix A. In a nutshell, the variance decomposition delineates how much the cross-sectional variations of the DLI can be attributed to the cross-sectional variations of the three variables.

Insert Table VI about here

Several observations emerge from the variance-decomposition results in Table VI. First, financial

[19] To be more precise, $\mu_E - r = \frac{\partial E}{\partial V}\frac{V}{E}(\mu - r)$ where E denotes equity value and μ_E denotes equity return and $\frac{\partial E}{\partial V}$ measures the sensitivity of equity value with respect to the underlying asset value V.

[20] To be precise, $\sigma_E = \frac{\partial E}{\partial V}\sigma_A$ where σ_E measures the stock return volatility.

leverage contributes to approximately 50 percent of the cross-sectional variation of DLI, regardless whether we focus on the whole sample or the subsample of firms with high DLIs. Consistent with prior empirical evidence in Altman (1968) and Shumway (2000), among others, financial leverage is the most salient proxy for default or financial distress risk. Second, Vassalou and Xing (2004) highlights the importance of firm level volatility as a determinant of default risk. We find even though asset volatility contributes modestly (around 20 percent) to the cross-sectional variations in DLI of the overall sample, its contribution in the high DLI subsample (the sample of interests for this paper) is much less. In the top one-third of the sample (as in Panel B) with the highest DLI, it only contributes about 7 percent, while in the top DLI quintile (as in Panel C), it contributes less than 4 percent. Third, past returns contribute the lion's share to the cross-sectional variation of DLI. In the overall sample, it contribute about 17 percent; but in the top one-third and one-fifth of the sample (the high DLI samples), it contributes 32 percent and 34 percent, respectively. The fact that past return is such an important determinant of DLI, especially for high DLI stocks, help to relate the high first month return of default risk stock to previous literature on return reversal. In the literature of short-term return reversal, past losers tend to demonstrate strong return reversal during the first month after portfolio formation (c.f. Jegadeesh (1990), Lehman (1990), Jegadeesh and Titman (1995), and Bessembinder and Hertzel (1993) in which they show significant negative autocorrelations in returns at various frequencies). In the remainder of this subsection, we verify that the return of the highest-DLI stock decile displays a short-term return reversal pattern, likely driven by a liquidity shock due to a clientele change. This observation accords well to the general findings in Avramov, Chordia and Goyal (2005), who show that temporary price pressure on illiquid stocks help to explain the short-run return reversal.

Our variance decomposition exercise shows that past return contributes substantially to high DLI. Since past return is negatively related to DLI, we expect high DLI stocks to be past losers. To confirm this, we compute the equally-weighted average return during the portfolio formation month for each DLI-decile. The results are provided in Table VII, Panel A .

Insert Table VII about here

The results confirm that in general there is indeed a negative relationship between DLI and past return. In particular, stocks in the highest DLI decile earn an average return of -3.58% during the portfolio formation month; They are clearly recent losers. They also earn the highest return (2.1%) during the first month after portfolio formation. This return pattern is consistent with the short-term return reversal previously documented in the literature.[21]

Panel B of Table VII displays the probability transition matrix of a stock moving from DLI decile i during the month immediately prior to the portfolio formation month $(t-1)$, to DLI decile j during the portfolio formation month (t). All probabilities in the same row should therefore add up to 1. As shown in the last column, about 17% of the stocks in the highest-DLI portfolio migrated from other deciles and are associated with larger increases in DLI. We label these stocks "new" high DLI stocks and the remaining 83% of the stocks in the highest-DLI portfolio "old" high DLI stocks. The "new" high DLI stocks display more pronounced return reversal patterns. On average, they suffer a larger return loss during the portfolio formation month (as in the last column of Panel C) and have higher positive returns during the month after (as in the last column of Panel D).[22] Panel E reports the corresponding Fama-French three-factor risk-adjusted returns during the first month after portfolio formation $(t+1)$. Again, only stocks that experience sharp increase in default risk (stocks moving from DLI decile 9 to decile 10 or from DLI decile 8 to decile 9) have significant positive risk-adjusted first-month returns.[23] Apparently, the first-month high return on the highest-DLI portfolio is mainly driven by the "new" high DLI stocks as the risk-adjusted return on "old" high DLI stocks is not significantly positive.

Panel A of Table VII also documents various characteristics of the 10 DLI-sorted portfolios. Consistent with Vassalou and Xing (2004), the highest-DLI stocks are associated with the smallest size and highest book-to-market ratios. Not surprisingly, high DLI stocks also trade at low prices.

[21] Stocks with the lowest DLI also demonstrate some degree of return reversal: they earn a high return of 2.48% during the portfolio formation month and a low return of 1.13% during the following month.

[22] A notable exception is a stock that migrates from decile 1 to decile 10 within a month. However, such stocks are too scarce (28 out of almost 900,000 stock/month observation) to let us draw any reliable inference.

[23] Stocks that experience sharp decrease in default risk (stocks moving DLI decile 10 to decile 9 or from DLI decile 9 to decile 8) exhibit symmetric return reversals: they are past winners during portfolio formation month but significantly under-perform during the first month after portfolio formation (the risk-adjusted returns are significantly negative). Such return pattern can be explained a similar clientele change. Institutional investors would like to hold a financially distressed stock as the optimal portfolio decision rule suggests but they cannot because of various investment restrictions. Therefore, as a stock's default risk decreases sharply, investment restrictions become non-binding and institutional investors start buying the stock. Such buying pressure pushes up the stock price during portfolio formation and leads to lower return during the first month after. We thank Anthony Lynch for pointing out this explanation.

In fact, both mean and median price decreases monotonically with DLI. The highest DLI stocks trade at a mean of \$3.58 and a median of only \$2.37.[24] Seguin and Smoller (1997) also find that "penny stocks" (by definition those less than three dollars) listed on NASDAQ are more likely to be delisted for distress related reasons. This is consistent with our finding that a high-DLI stock is associated with low trading price. The low trading price makes the percentage transaction cost much higher for financially distressed stocks, thus making them more illiquid at the same time.[25] We consider the "illiquidity" measure suggested by Amihud (2002):[26,27]

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

We average the daily absolute value of the ratio between return and dollar trading volume of individual stocks during the portfolio formation month t to get the Amihud measure for month t – $Amihud_t$. In order to construct the Amihud measure, we use the filtering rules suggested by Amihud (2002), except that we do not exclude NASDAQ stocks and stocks traded at less than five dollars. In particular, we require that individual stocks must be traded on the stock exchanges for at least 200 days. Furthermore, to minimize the influence of special liquidity provisions from the market makers during the IPO process (see Ellis, Michaely and O'Hara, 2000), we exclude the first 250 observations when a firm first enters CRSP in our sample.[28] The illiquidity measures

[24] One common practice in empirical asset pricing studies is to exclude penny stocks in light of liquidity related concerns. However, this practice, in the context of the current paper, amounts to excluding a large number of financially distressed stocks – the subset of stocks we are most interested in. Therefore, as in Vassalou and Xing (2004), we decide not to apply any price filter. Instead we explicitly examine and control for the liquidity effects associated with these stocks. If we exclude stocks traded less than 5 dollars, the highest DLI stocks in the remaining sample do not earn significantly higher returns even during the first month after portfolio formation, consistent with the evidence reported in Garlappi, Shu and Yan (2005).

[25] As in Panel B of Table VI, the percentage bid-ask spread monotonically increases in DLI, and the percentage bid-ask spread for stocks in DLI-decile 10 is at least 8 times higher than that for stocks in DLI-decile 1.

[26] To measure the liquidity effects precisely, we would hope to use some versions of liquidity measures constructed from a market intraday database like ISSM and TAQ. However, these data have relatively short time horizons. Left with some liquidity measure constructed from daily return and trading volume data, we decide to use the Amihud measure. Hasbrouck (2005) show Amihud measure works remarkably well compared to tick-by-tick estimated liquidity measures.

[27] Pástor and Stambaugh (2003) adjust the liquidity measure by the total market capitalization to account for the increased trading activities over time. Acharya and Pedersen (2005) apply an affine transformation to the original Amihud measure in order to compute a sensible liquidity-adjusted return. Since we focus on the relative liquidity of a stock in a cross-section in which these adjustments have little impact, we decide to work with the original Amihud measure.

[28] To assess the robustness of our empirical measures, we also consider a few variants of the above construction: (1) We experiment with excluding the top and bottom 1 percent of the annual observations to mitigate the influence of outliers. (2) We replace the missing value of the daily liquidity measure with concurrent year minimum, mean, median and maximum illiquidity measures. All of the results are quantitatively and qualitatively similar.

of individual stocks are then equally-weighted to obtain the illiquidity measure at the portfolio level. The results are striking: both versions of Amihud's illiquidity measures increase almost monotonically with the DLI.[29]

Panel A of Table VII also reports the average idiosyncratic risk measures for stocks in 10 DLI-sorted deciles. 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.[30] Clearly, the idiosyncratic risk measure increases monotonically with DLI. In particular, for stocks with the highest DLI, nearly 97% of the total risk is idiosyncratic in nature. Finally, we show that high-DLI stocks receive little wall street coverage. As a proxy for Wall Street research coverage, for each stock each month, we check whether analyst earnings forecast is made for the firm's announced past quarter earning and, if so, compute the number of unique analysts. The earning forecast data is obtained from I/B/E/S from 1984 to 1999. For each of the 10 DLI sorted portfolio, we report the average percentage of stocks receiving analyst coverage and the average number of analysts for the stocks receiving coverage at all in Panel A of Table VII. As expected, both coverage measures decrease with DLI. Amongst stocks in the lowest-DLI decile, 74% receive analyst coverage – 5.4 analysts on average following each stock, if the stock receives analyst coverage at all. In sharp contrast, amongst stocks in the highest-DLI decile, only 20% receive analyst coverage and there are only 2.5 analysts per stock, if the stock receives analyst coverage at all.

3.2 Institutional selling pressure

In summary, the highest-DLI stocks are characterized by small market capitalization, high book-to-market ratio, high idiosyncratic risk, low trading price, low level of liquidity and low Wall Street coverage. Institutional investors such as pension funds and mutual funds are often restricted to stocks that are liquid, issued by high-quality companies, with considerable market capitalizations, low idiosyncratic risk and stable dividend payouts (c.f. Almazan, Brown, Carlson and Chapman,

[29] The Amihud measures for NASDAQ stocks are likely to be underestimated due to "double countings" in their reported trading volumes. We verify the positive relation between the Amihud measure and DLI in a subsample of only NYSE/AMEX stocks.

[30] The exact regression equation is (6).

2004). Table VIII lists a few examples of such restrictions by institutional investors. A financially distressed stock will unlikely satisfy these restrictions; it is not surprising then to observe a clientele change for these stock as the institutional investors sell it from their current holding.

Insert Table VIII about here

3.2.1 Selling pressure from mutual funds

Institutional investors may include mutual funds, pension funds and hedge funds, among others. We decide to focus on mutual funds because they constitute a relatively homogenous group of investors and have regular disclosures as required by SEC.[31] It turns out our conjecture about the clientele change is true at least for mutual funds as a group. Mutual funds are likely to be a group of investors facing many potential investment constraints. For example, there is anecdotal evidence that a typical mutual fund in general avoids low priced stocks so as not to be looked as "speculative" or "imprudent".[32,33] For example, between 1980 to 2005, in the sample of stocks held by all mutual funds and which can be matched with CRSP monthly stock file, merely 3.73 percent of stocks are priced less than 5 dollar as of reporting date while 90.38 percent of stocks are priced more than 10 dollars.[34] We choose to focus on mutual funds as a clientele and we infer their buy and sell decisions by looking at the aggregate mutual fund holdings and holding changes when stocks become financially distressed.

The mutual fund holding data come from the CDA/Spectrum mutual fund holding database,

[31] We also obtain qualitatively similar results using CDA/Spectrum Institutional 13F Stock Holdings and Transactions database, where the quarterly transactions and holdings by institutional investors including mutual funds, banks, insurance companies, pension funds and endowment funds are recorded.

[32] Mutual funds may "window dress", i.e., they sell recent losers before reporting their holdings (c.f. Haugen and Lakonishok (1988) and Meier and Schaumburg (2005)). This could be another reason why increase in financial distress could trigger a clientele change and selling by mutual funds, as financially distressed stocks are likely to be recent losers.

[33] The eventual delisting may be very costly to the stockholders and SEC rules preclude most institutions from holding unlisted shares (cf. Macey, O'Hara and Pompilio, 2004). In addition, liquidity tend to dry up when delisted stocks are later on traded in the OTC Bulletin Board and/or the Pink Sheets(cf. Harris, Panchapagesan and Werner, 2004). For the above reasosns, some institutions may want to sell the stocks even before the eventual delisting.

[34] Even some very specalized micro-cap investors generally hold a small percentage of low priced stocks. For example, according to its prospectus, during the period from 09/1982 to 06/2005, for all shares held by Dimensional Fund Advisor Micro-cap fund (Ticker Symbol: DFSCX), about 6% of the stocks were less than 1 dollar, 13% of the stocks were greater than 1 dollar but less than 3 dollar, another 13% of the stocks were greater than 3 dollar but less than 5 dollar, and the rest were all greater than 5 dollars. In all cases, DFA holds less than 1% of outstanding shares as reported by CRSP. DFA invests only in the bottom 4% of market capitalization stocks in this series of micro-fund.

which collects the holding information from the N30-D filings to the Security and Exchange Commission (SEC). A detailed description of the database can be found in Wermers (1999). As our mutual fund holding database only starts at 1980, we only consider the sample from 1980 to 1999. Although typically stocks are likely to be held by a large number of mutual funds, there are number of stocks which are only held by one or two mutual funds recorded by the CDA/Spectrum database. A possible explanation for this observation is that small holdings are exempted from reporting by SEC regulations, giving us a lower-end truncated sample.[35] Therefore, it is likely the number of mutual fund shareholders are under-stated according to CDA/Spectrum but the likely impact should be relatively small. Without further assumptions, it is not entirely clear how such reporting practice may influence the inference of current empirical study. To assess such bias, we further sort the stocks into three groups based on the breadth of ownership as a robustness check: Low refers to ones for which the underlying shareholders is less than or equal to 2; Medium refers to ones for which the underlying shareholders between 3 and 7 (inclusive); and High refers to ones for which the underlying shareholders greater than or equal to 8. These break points roughly match the 33 percentile and 67 percentile of underlying mutual fund shareholders across all stocks and all years in our sample. We report the statistics from the full sample (1980 - 1999), and also two subsamples (1980 - 1989 and 1990 - 1999) to ensure that the results are not driven by later period when the number of mutual funds dramatically increases. A final caveat is in order. Because we only look at the aggregate mutual fund holdings and holding changes in the event of stocks' financial distress, we cannot say much about intra-fund flows of share holdings.

At any quarter, we sum across the reported number of shares held by individual mutual funds and obtain the aggregate holdings of mutual funds. We examine two aspects of the aggregate mutual fund holdings and holding changes of the financially distressed stocks. We first investigate the aggregate mutual fund holdings and holding changes of *all* high DLI stocks. At a given quarter Q, we identify all stocks which fall into the highest DLI decile ranking during any month of the current quarter and record the aggregate mutual fund holdings ($Holding_{i,Q}$). Then we track all high DLI stocks' aggregate mutual fund holdings during the preceding quarter ($Holding_{i,Q-1}$). The

[35] 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 (or less than $200,000 principal amount in the case of convertible debt securities) and less than $200,000 aggregate fair market value (and option holdings to purchase only such amounts)."

aggregate holding change ($\Delta Holding_i$) is defined as

$$\Delta Holding_i = Holding_{i,Q} - Holding_{i,Q-1} \tag{3}$$

and we conjecture that mutual funds on average decrease their holdings of the stock ($\Delta Holding_i < 0$) for high DLI stocks if mutual funds on average avoid holding financially distressed stocks.

We also examine the aggregate mutual fund holdings and holding changes of *recent* high DLI stocks. That is, at a given quarter Q, we only identify stocks which were not in the highest DLI decile in *all* months during the preceding quarter, but recently migrated into high DLI decile during *any* month in current quarter. We compare the mutual fund holdings before ($Holding_{i,Q-1}$) and after ($Holding_{i,Q}$) the stocks become financially distressed in current quarter, and compute the aggregate mutual fund holding changes ($\Delta Holding_i$) as

$$\Delta Holding_i = Holding_{i,Q} - Holding_{i,Q-1} \tag{4}$$

We also conjecture that the mutual funds on average decrease their holdings of the stock ($\Delta Holding_i < 0$) if the stock becomes financially distressed. In addition, we expect the holding decreases to be sharper for *recent* high DLI stocks if the clientele change is triggered by a sudden increase in financial distress.

Insert Table IX about here

The results presented in Table IX consistently supports our conjecture that when stocks becomes financially distressed, there is a change of clientele, as proxied by mutual fund aggregate ownership, across all sample periods and all levels of the breadth of ownership. On average, mutual funds avoid holding high DLI stocks. In the full sample period, mutual funds decrease their holdings of *all* high DLI stocks by 0.67% of all shares outstanding on average within a quarter; and for *recent* high DLI stocks, mutual funds decrease holdings by 0.95% within one quarter.[36] The decrease of holdings is particularly pronounced for high breadth of ownership stocks. In the full sample period, mutual

[36] The mutual fund holding change does not differ significantly across different calendar quarters. For *all* high DLI stocks, the mutual fund change is −0.6%, −0.58%, −0.72% and −0.76% during calendar quarter 1 to 4. For *recent* high DLI stocks, the mutual fund change is −1%, −0.7%, −1.1% and −1.0% during calendar quarter 1 to 4. Therefore, the mutual fund holding change result is unlikely to be driven primarily by large year-end selling for tax reasons as documented by Branch (1977), and more recently Grinblatt and Moskowitz (2004).

fund decreases holdings of all high DLI stocks with high number of ownerships by 1.87% of all shares outstanding on average within a quarter; and for recent high DLI stocks with high breadth of ownership, mutual funds decrease holdings by 2.36% within one quarter. All these reported changes are statistically significant at 1 percent significance level. We also verify that the decrease in mutual fund holding mostly occurs during the quarter when the stock becomes financially distressed (see Panel C and D of Table IX). For *all* high DLI stocks, the absolute quarterly mutual fund holding change is below 0.11% during each of the four quarters immediately following the event quarter (Q). For *recent* high DLI stocks, although there are still significant decrease in mutual fund holding during the first two quarters immediately following the event quarter (Q), the magnitude of such decrease is much smaller (0.13%) as compared to the decrease during the event quarter (0.95%).

To show the result on mutual fund selling is not driven by a few outliers, we plot the histogram of changes in individual mutual fund holdings for high DLI stocks. Specifically, for each stock i, mutual fund j, at quarter Q, we compute the holding change $\Delta Holding_{i,j,Q}$ as:

$$\Delta Holding_i = Holding_{i,j,Q} - Holding_{i,j,Q-1} \tag{5}$$

and plot the distribution of all $\Delta Holding_i$ using a histogram in Figure 3. It turns out that more than 73% of the individual mutual fund change is negative, indicating heavy selling pressure. In addition, there are very few outliers.

Insert Figure 3 about here

3.2.2 Evidence of institutional selling pressure at a higher frequency

Given the quarterly mutual fund holding reporting frequency, we cannot rule out the possibility that mutual fund holding changes actually occur during the month prior to the increase in DLI. It would be better to examine the institutional trading activities during the same month when the 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's customers consist of over 200 financial institutions that collectively transact over $4.5 trillion in equity trading volume prior to the acquisition by ITG, Inc.[37] The Plexus group data have been used by Keim and Madhavan (1995) and Conrad, Johnson and Wahal (2003) among others.[38] The Plexus group dataset examined in this section is a combination of the one used by Keim and Madhavan (1995) (which covers from Q2 of 1991 to Q1 of 1993) and the one used by Conrad, Johnson and Wahal (2003) (with the coverage from Q1 of 1996 to Q1 of 1998). The dataset records the details (time, size, buy/sell indicator, type of the order among others) of every institutional order for all the institutions that Plexus Group monitors. It also records when and how many orders actually get executed. Therefore, for every stock in our sample during portfolio formation month, we are able to compute the aggregate net buy/sell orders (as percentage of total number of shares outstanding) submitted by institutions and the actual aggregate shares bought/sold (again as percentage of total number of shares outstanding) by institutions at monthly frequency. We can then average these two institutional trading measures first across all stocks at portfolio level and then across time. The results for the 10 DLI deciles and the portfolio of "new" high DLI stocks are presented in Table X. Though we have made a refined and precise measurement of institutional trading, the trade-off for using the Plexus Group dataset is a short sampling period and the fact that institutions monitored by Plexus group is only a subset of the universe of all institutions.[39]

Insert Table X about here

Table X confirms a significant selling pressure for a stock during the month when the stock's DLI increases. Panel A presents the result for the full Plexus Group dataset. A negative number indicates net selling. For both all high DLI stocks and "new" high DLI stocks, the institutions submit significantly more sell orders and, on average, sold them. Since the coverage of Plexus Group dataset is significantly smaller during the first sub-sample (from Q2 of 1991 to Q1 of 1993), the institutional trading measures could be considerably noisy especially for "new" high DLI stocks. For example, the average number of "new" high DLI stocks with Plexus Group coverage comes out

[37] See http://media.corporate-ir.net/media_files/IROL/10/100516/PDF/173370.pdf.

[38] A detailed description and summary statistics of the Plexus Group data can be found in Conrad, Johnson and Wahal (2003) for example.

[39] By early 2003, Plexus Group analyzed 25% of exchange traded volume worldwide. Early year coverage of Plexus Group data is significantly less in total volumes, but still substantial. Given said, we believe our sample is representative of US equity institutional transactions.

at only 2 for the first sub-sample. The coverage of Plexus Group dataset improves significantly during the second sub-sample (Q1 of 1996 to Q1 of 1998). For example, the average number of "new" high DLI stocks with Plexus Group coverage is 18 during the second sub-sample. For this reason, we also report the results during the second sub-sample separately in Panel B. The institutional trading measures during the second sub-sample, arguably less noisy, are qualitatively similar to those in the full sample. For both all high DLI stocks and "new" high DLI stocks, there is significant selling pressure during the portfolio formation month. In addition, the selling pressure is more significant for "new" high DLI stocks as we would expect.

3.3 Lack of ready buyers

The selling of financially distressed stocks by institutional investors such as mutual funds is unlikely to be absorbed by ready buyers without moving the price. The market makers, afraid of the selling being information-driven, will only want to buy the stock with price concession. Outside investors are unlikely to move in their capital immediately as argued by Berndt, Douglas, Duffie, Ferguson and Schranzk (2005). It takes time and human capital for an investor to identify a profitable opportunity and then mobilize capital (capital immobility).[40] We think this is especially true for financially distressed stocks. The success and failure of distressed securities investing depend on the investor's efficiency and effectiveness in uncovering and analyzing all of 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".[41] Gathering and analyzing such firm specific information is a daunting task and very time consuming, requiring a large amount of human capital. The absence of Wall Street research coverage on distressed firms makes this task even harder.[42]

[40] Consistent with the capital immobility argument, Duarte, Lonstaff and Yu (2005) find that the fixed-income arbitrage strategies requiring more "intellectual capital" to implement tend to produce significant risk-adjusted returns and the risk-adjusted excess returns from these strategies are related to capital flows into fixed-income arbitrage hedge funds.

[41] See "Distressed Securities Investing" by Dion Friedland, Chairman of Magnum Funds.

[42] "The lack of Wall Street coverage is due to the fact investment banks tend not to view companies emerging from bankruptcy as potential clients. Further, these companies are tainted in general by the financial distress and thus do not make it onto the list of companies to which Wall Street investment banks allocate expensive research resources..."

When there is large selling pressure and lack of immediate ready buyers, the stock price will be temporarily depressed. The price concession may attract new buyers including arbitrageurs to enter the market and the price will soon recover. Pástor and Stambaugh (2003) focus on liquidity shocks that play out within the span of a day. Keim and Madhavan (1996) does this as well, showing that the price impact of a block sell order lasts on average for just one day. To examine the duration of liquidity shock for financially distressed stocks, we trace out the first 20 daily returns after portfolio formation for stocks in the highest DLI portfolio. Figure 4 plots these daily returns. Consistent with Pástor and Stambaugh (2003) and Keim and Madhavan (1996), we observe a strong first day return reversal of, on average, more than 60 bps for financially distressed stocks. However, the above average return lasts until the second week after portfolio formation, which indicates a persistence in the liquidity shock.

Insert Figure 4 about here

Panel A of Table II show that financial distressed stocks are usually penny stocks associated with very high idiosyncratic risks and little Wall Street coverage. These stock characteristics contribute to the persistence of the liquidity shock for financially distressed stocks. From the perspective of the market maker, higher idiosyncratic risk means larger amount of nondiversifiable risk in his stock inventory. In response, the market maker is less willing to provide liquidity temporarily as predicted by Spiegel and Subrahmanyam (1995) and Spiegel and Wang (2005). Our idiosyncratic risk measure can also be interpreted as a proxy related to the proportion of private information (c.f. Durnev, Morck, Yeung, and Zarowin (2003)). It follows that the high idiosyncratic risk measure in the high DLI portfolio indicate that a large fraction of the information is private in nature.[43] Moreover, the difficulty of collecting and analyzing information specific to distressed stock results in a higher degree of information uncertainty. Market makers, in order to protect themselves from information asymmetry in such a uncertain environment, will impose higher trading costs for the distressed stocks over a longer period of time, as argued in Sadka and Scherbina (2004). From the

– "Distressed Securities Investing" by Dion Friedland, Chairman of Magnum Funds.

[43] Given this interpretation, it is easy to understand why the liquidity shock is particularly pronounced among the high DLI portfolios as private information is usually associated with larger price impact of trade as in Kyle (1985). Bessembinder, Chan, and Seguin (1996) also provide some supporting evidence. They find firm-specific information to have the largest proportional effect on the volume of small firms, which is consistent with the increased turnover we documented for financially distressed stocks.

perspective of an arbitrageur, higher idiosyncratic risk makes it difficult to locate similar stocks to short in the arbitrage portfolio as argued in Wurgler and Zhuravskaya (2002). This difficulty, together with larger percentage transaction costs associated with low-priced financial distressed stocks, keep risk-averse arbitrageurs from investing immediately after the stock becomes distressed, as argued in the "limits-to-arbitrage" literature (c.f. Shleifer and Vishny,1997) and price recovery takes longer.[44]

To summarize the findings so far, a sharp increase in a firms' financial distress risk is likely to trigger a clientele change of its stockholders. Selling off amongst existing institutional investors such as mutual funds,a surplus unlikely absorbed by ready buyers, generates a liquidity shock. The subsequently temporarily depressed stock price will induce the market maker to step in and take the other side. The liquidity will improve after a while and the prices will bounce back, as outside investors recognize the opportunity and gradually move their capital to the stock. In the next subsection, we examine the trading volume, trading cost, order imbalance and level of liquidity during such time, providing additional evidence to support the presence of liquidity shock.

3.4 Changes in liquidity-related characteristics during the liquidity shock

Due to the liquidity shock associated with a financially distressed stock, an investor wishing to sell a significant quantity of it will suffer a price concession, and conversely, an investor ready to buy it (therefore provide liquidity) will be rewarded by the later price recovery. Such liquidity shock has been discussed in the model of Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993). One implication of the model is that large trade by liquidity investors leads to a temporary divergence between price and fundamental value. This implies that price concessions accompanied by high volume will tend to be reversed. Empirically, Conrad, Hameed, and Niden (1994) report that stocks with high trading activity are likely to experience short-term return reversal and stocks with low trading activity short-term return continuation. We examine the trading activity of financially distressed during the liquidity shock and document a similar pattern. Panel A of Table XI compares the trading volume for stocks in various DLI deciles during three two-month-periods:

[44] Consistent with the limits-to-arbitrage arguement, we show that among "new" high DLI stocks, those with higher arbitrage risk measures (Wurgler and Zhuravskaya, 2002) exhibit larger return reversals.

(1) the two months prior to the portfolio formation month ([-2,-1]); (2) the portfolio formation month and the first month after portfolio formation ([0,1]); (3) the second and third month after portfolio formation ([2,3]). The trading volumes are adjusted for changes in the total number of shares outstanding. Finally, all trading volumes are normalized by the trading volume during the two months prior to the portfolio formation month ([-2,-1]). "New" high DLI stocks are stocks which have just recently entered the highest-DLI decile during the portfolio formation month. Although the normalized trading volumes during month ([0,1]) are in general decreasing in DLI, this pattern reversed for the highest DLI-decile: we observe an increase in trading for stocks in the highest-DLI decile around the liquidity shock. This pattern is mainly driven by "new" high DLI stocks. For this subset of stocks that have recently become financially distressed, we observe a significant increase in trading activity only around the liquidity shock, and not afterwards, consistent with the implication of the model by Campbell, Grossman, and Wang (1993).

Insert Table XI about here

Financially distressed stocks also experience a large increase in trading cost during the liquidity shock. We measure the trading cost using the percentage bid-ask spread, defined as the ratio between the quoted bid-ask spread and the midpoint of the quoted bid and quoted ask. The percentage bid-ask spread is computed using intraday quote data from TAQ (after 1993) and ISSM (before 1993). The sampling period for NYSE stocks is from 1983 to 1999 and the sampling period for NASDAQ stocks is from 1987 to 1999. The average spreads are reported in Panel B of Table XI. As we expect, the spread measure increases monotonically with DLI, verifying that financially distressed stocks are more costly to trade. More interestingly, while the trading cost measure hardly changes during the portfolio formation month for stocks in DLI decile 1 to 9, it increases significantly for the financially distressed stocks in DLI-decile 10. Again, such increase in trading cost is mainly driven by "new" high DLI stocks whose percentage bid-ask spread increases by more than 1% with an associated t-value above 10. This increase is not surprising given the fact that "new" high DLI stocks are recent losers.

If heavy selling by institutional investors leads to price concession and subsequent buying by outside investors leads to later price recovery, we would expect more sell-initiated trades during portfolio formation month and more buyer-initiated trades during the month after formation for financially distressed stocks. This is exactly what we find using order imbalance measures developed in Chordia, Roll and Subrahmanyam (2002). The time series of the order imbalance measures start from 1988 and end in 1998. $OIBSH1_t$ is the buyer-initiated shares purchased less than the seller-initiated shares sold on day t. $OIBSH2_t$ is $OIBSH1_t$ scaled by the total number of shares traded on day t. We average both variables first within each month and then within each DLI-sorted portfolio to get monthly order imbalance measures for each portfolio. The results are reported in Panel C of Table XI. For stocks in the highest-DLI decile, $OIBSH1$ is negative during portfolio formation month which means more trades are seller-initiated, and $OIBSH1$ is positive during the month after formation which means more trades are buyer-initiated. The change in $OIBSH1$ is positive and significant. In addition, across all DLI-sorted deciles during the formation month, $OIBSH1$ is only negative in the highest-DLI decile. We also observe significantly more buyer-initiated trades after portfolio formation for stocks in the highest-DLI decile with the relative order imbalance measure ($OIBSH2$). Finally, we show that this change in order imbalance is more pronounced for "new" high DLI stocks only recently entering the highest-DLI decile during the portfolio formation month. Changes in both order imbalance measures are more positive and significant.

Panel D reports the average realized (half) spreads (scaled by traded price) for each DLI decile and the portfolio of "new" high DLI stocks around portfolio formation month. The realized spread is originally developed by Huang and Stoll (1996) as a direct measure of what the liquidity supplier actually earn. The realized spread is computed using intraday trade and quote data from1983 to 1999.[45] If high-return on the high DLI stocks is related to compensation for liquidity provision, we would expect the average realized spread for these stocks to be much higher around the liquidity shock. Indeed, the average realized spread for high DLI stocks is higher around portfolio formation (month = 0 and 1) and such pattern is again driven by "new" high DLI stocks. The average realized spread for "new" high DLI stocks increases significantly during the portfolio formation month when there is a liquidity shock, reflecting an increased compensation for liquidity provision required by liquidity suppliers. The higher realized spread persists during the first month after portfolio formation and drops to its normal level.

[45] See Huang and Stoll (1996) for detailed estimation procedure. The time horizon used for the estimation is 30 minutes to account for infrequent tradings.

In addition, we expect the liquidity risk of a stock to fluctuate around the liquidity shock. We measure the stock liquidity risk using the liquidity beta proposed by Pástor and Stambaugh (2003). The liquidity beta measures the exposure of the stock to an aggregate economywide liquidity factor. Specifically, the liquidity beta n months after portfolio formation for portfolio i is defined as the slope coefficient (β_i^n) in the following regression:

$$r_{i,t}^n = \alpha_i^n + \beta_i^n L_t + \beta_{i,M}^n MKT_t + \beta_{i,S}^n SMB_t + \beta_{i,H}^n HML_t + \varepsilon_{i,t},$$

where $r_{i,t}^n$ is the excess return nth month after portfolio formation; L_t is the innovation in the aggregate liquidity factor defined by Pástor and Stambaugh (2003); and MKT, SMB and HML are the Fama-French three factors. We examine four liquidity betas: (1) the pre-formation liquidity beta which is the average liquidity betas during the three months prior to the portfolio formation month (month [-3,-1]); (2) the liquidity beta during the portfolio formation month (month 0); the liquidity beta during the first month after the portfolio formation month (month 1); and (4) the post-formation liquidity beta which is average liquidity betas during the second to fourth month after portfolio formation (month [2,4]).

Insert Figure 5 about here

Figure 5 plots the four liquidity betas for High DLI stocks (all stocks in the highest-DLI decile), New High DLI stocks (subset of High DLI stocks that only recently entered the highest-DLI decile during the portfolio formation month) and Old High DLI stocks (the remaining High DLI stocks that also belong to the highest-DLI decile during the portfolio formation month). For High DLI and New High DLI stocks, their liquidity betas display an inverse-V shape around portfolio formation. The liquidity betas increase significantly during the portfolio formation month, which indicates a drop in stock liquidity risk, coinciding with the price concession. The liquidity betas then drop significantly during the first month after portfolio formation and return to their normal levels thereafter. The decreases in liquidity betas indicate an improvement in stock liquidity risk, coinciding with the price recovery. As expected, the inverse-V shape is more pronounced for New High DLI stocks. In contrast, the liquidity betas of Old High DLI stocks do not vary significantly around portfolio formation. Panel E of Table XI reports the four liquidity betas for all 10 DLI-sorted portfolios as well as the New DLI stocks. It also reports in the changes in liquidity betas from period to period. The t-values associated with these changes are computed using the Newey-West standard error estimators with three lags. Across all 11 portfolios, we observe statistically significant fluctuations in liquidity betas around portfolio formation only for the High DLI stocks and the New High DLI stocks.

That stock price reversal coincides with changes in liquidity beta is consistent with the theoretical model and empirical findings by Pástor and Stambaugh (2003). Since liquidity beta carries a positive risk premium, when the liquidity beta of a stock increases, the stock becomes more risky, *ceteris paribus*, and its discount rate goes up, resulting in a price drop. Conversely, as the liquidity beta later drops, the discount rate also decreases and the stock price will recover. The resulting high return on the stock during the first month after portfolio formation is therefore consistent with the dynamic decrease in the liquidity beta. However, an unconditional asset pricing test which ignores the dynamic nature of the liquidity risk, is likely to produce spurious results. As we can see from Panel E of Table XI, stocks in the highest-DLI decile having the smallest liquidity beta earn the highest return while stocks in the lowest-DLI decile having the largest liquidity beta earn a lower return. An unconditional cross-sectional regression where first-month returns are regressed on the liquidity betas will likely produce a negative risk premium on the aggregate liquidity factor, which is counter-factual. This is again because the large first-month return on high-DLI stocks is mainly driven by the price recovery following the temporary liquidity shock, rather than a permanent liquidity risk premium as can be captured by the loading on the aggregate liquidity factor.

3.5 Characteristics regression

In this subsection, we want to directly examine various stock characteristics all how they explain next month stock returns. Since various characteristics are highly correlated with each other at the portfolio level (as in Panel A of Table VII), sorting stocks into portfolio according to one characteristic will inevitably induce dispersion along the dimensions of other characteristics. Therefore, double-sorting is less effective in controlling for these characteristics. We therefore use a cross-sectional regression approach at individual stock level. If the first-month high return on financially distressed 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 with the presence of other stock characteristics. On the other hand, if the first-month high return is a result of of the liquidity-induced price reversal, we would expect *Pastret* to always be strongly significant. Since a larger price concession will be followed by a larger price recovery, *ceteris paribus*, the past one-month return is negatively related to the next-month return in a mechanical way Finally, as financially distressed stocks are typically illiquid, we would also expect the liquidity measure *Amihud* to be significant in the regression as in Amihud (2002) and Acharya and Pedersen (2005), among others.

The cross-sectional regression approach is similar to Brennan, Chordia and Subrahmanyam (1998). We control for systematic factor risk by first computing the Fama-French three factor alpha.[46] The factor loadings at month m are computed using rolling window regression from $m - T - 1$ to $m - 1$. For each month from 1970/01 to 1999/12, we run a cross-sectional regression of the next month alpha on various stock characteristics from the current month. All variables are cross-sectionally demeaned so the intercept term of the regression is zero. In addition, the stock characteristics are standardized so the regression slope coefficient of a variable can be interpreted as the impact on the alpha 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: *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/Ms.

Insert Table XII about here

Panel A of Table XII reports the correlations among these five characteristics in both the full sample and the top DLI-quintile subsample. Then signs of these correlations are all consistent with the pattern reported in Panel A of Table VII. *DLI* is highly correlated with *Size* and B/M. *Amihud* and *Pastret*, on the other hand, are less correlated with other characteristics at individual stock level.

[46] The results are qualitatively similar if the first month returns instead of alphas are used.

Panel B of Table XII reports the regression results where factor loadings are computed using monthly returns in a rolling window of 5 years. In the first three regressions (Models 1 to 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 alpha. *Pastret* is strongly significant (t-value of -9.7) and *Amihud* is slightly more significant than DLI (t-value of 3.56 for *Amihud* v.s. 3.16 for DLI). DLI, however, becomes insignificant with the presence of other characteristics (Model 4 and 5). Specifically, DLI becomes insignificant once *Pastret* and *Amihud* are included (Model 4). In addition, since all three characteristics are correlated with *Size* and B/M, both of which are shown to have explanatory power on alpha, Model 5 controls for the *Size* and B/M characteristics by including them in the regressions. In Model 5, DLI is not significant and assumes the wrong sign but *Pastret* and *Amihud* are still significant. Finally, since the liquidity-shock-induced price reversal is likely to be more pronounced for illiquid stocks, we would expect a interaction term between *Pastret* and *Amihud* to be negative and significant. This is indeed the case as in Model 6. The interactive term is highly significant and subsumes the explanatory power of *Amihud*. We also repeat the regressions in the sample we are more interested in – the group of stocks in the highest DLI quintile. The results are qualitatively identical.

Since risk characteristics may change when a stock becomes financially distressed, factor loadings estimated using a rolling window of 5 years may not reflect the risk characteristics of the stock at portfolio formation. As a robustness check, we estimated the factor loadings using daily return in a much shorter rolling window of 6 months. Specifically, at each month m, for every stock with more than thirty valid observations, we estimate the following regression using daily excess returns and the Fama-French three factors over past 6 months:

$$\begin{aligned} R_{i,t} - R_{RF,t} &= \alpha + \beta_{i,0} MKT_t + \beta_{i,1} MKT_{t-1} \\ &\quad + \beta_{i,2}\left[\frac{MKT_{t-2} + MKT_{t-3} + MKT_{t-4}}{3}\right] \\ &\quad + h_{i,0} HML_t + h_{i,1} HML_{t-1} + h_{i,2}\left[\frac{HML_{t-2} + HML_{t-3} + HML_{t-4}}{3}\right] \\ &\quad + s_{i,0} SMB_t + s_{i,1} SMB_{t-1} + s_{i,2}\left[\frac{SMB_{t-2} + SMB_{t-3} + SMB_{t-4}}{3}\right] + \varepsilon_{i,t}, \quad (6) \end{aligned}$$

where MKT, HML and SMB are the daily market excess return factor, HML factor and SMB factor, respectively. To avoid overparameterizing the estimation equation, we also restrict the factors coefficients to stay the same for $t-2$, $t-3$ and $t-4$ as in Lewellen and Nagel (2005). To control for the nonsynchronous trading, we use the sum-beta method in Dimson (1979). After obtaining the estimates, we compute the "sum-beta" estimates for market excess return, HML and SMB factors as:

$$\begin{aligned} \hat{\beta}_i &= \hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2}, \\ \hat{h}_i &= \hat{h}_{i,0} + \hat{h}_{i,1} + \hat{h}_{i,2}, \\ \hat{s}_i &= \hat{s}_{i,0} + \hat{s}_{i,1} + \hat{s}_{i,2}. \end{aligned} \tag{7}$$

The alpha for the subsequent month $(m+1)$ is computed based on the following equation

$$\tilde{\alpha}_{i,m+t} = (R_{i,m+1} - R_{RF,m+1}) - \hat{\beta}_i MKT_{m+1} - \hat{h}_i HML_{m+1} - \hat{s}_i SMB_{m+1} \tag{8}$$

The regression results are presented in Panel C of Table XII and are qualitatively similar to those in Panel B. In summary, default risk as measured by DLI does not seem to provide additional explanatory power regarding next month alpha beyond *Pastret*, *Amihud*, *Size* and B/M. *Pastret*, however, strongly predicts the next month alpha on top of other characteristics. The liquidity measure, *Amihud*, also provides some additional predictive power. An interaction term between *Pastret* and *Amihud* is highly significant and subsumes the explanatory power of *Amihud*. These findings are consistent with the liquidity-shock based explanation for the high first-month return on the high-DLI stocks.

3.6 Additional Discussions

In Appendix B, we show that the first-month high return on financially distressed stocks are unlikely driven by bias through random bid-ask bounce or the high level of uncertainty associated with the distress event. In addition, we gauge the economic significance of the return and find outside investors unable to take advantage of the high return on financially distressed stocks after transaction cost. This finding has two implications. First, the high return and large Sharpe Ratio earned by high default risk stocks does not constitute a violation of efficient market hypothesis.

Second, only market makers, generically defined, are compensated by providing liquidity when it is most needed. Finally, we show that as market making becomes more competitive after mid-1997, the return earned by financially distressed stocks also drops, indicating a reduced compensation for liquidity provision.

4 Conclusion

Vassalou and Xing (2004) show that stocks of firms under financial distress, on average earn a large positive abnormal return during the first month after portfolio formation, even after adjusting for risk using standard asset pricing models. In this paper, we show that a sharp rise in a firm's exposure to financial distress risk triggers a clientele change for its stock, resulting in temporary selling pressure. For example, mutual funds significantly decrease their holdings of stocks from firms that experience sharp rises in their default likelihood measures. When the liquidity of the stock later improves, the stock price recovers, which contributes to the high return on financially distressed stocks during the first month after portfolio formation. Changes in various market microstructure attributes of a stock, such as trading volume, percentage bid-ask spread, realized (half) spread and order imbalance measures, are all consistent with there being such liquidity shock. Therefore, a major part of the high return on these stocks can be interpreted as reward for liquidity provision when it is most needed.

Consistent with this view, we find that the high returns on financially distressed stocks accrue during the first month following portfolio formation, but little during the months afterwards, although various risk characteristics hardly change. This result supports the claim in Campbell, Hilscher and Szilagyi (2005), and Garlappi, Shu and Yan (2005), that high default risk itself does not necessarily translate to high return in the future. In addition, we find that although the first month high return on the high-DLI stocks cannot be explained by the standard Fama-French three factors, when we skip a month, the second month return can be well explained by the three factors, and an aggregate default risk factor ceases to be significant in various asset pricing tests using the second month returns on portfolios sorted on DLI. Collectively, evidence so far suggests that there is no need for a separate aggregate default risk factor in reduced form asset pricing models. Our findings also highlight the time-varying nature of a stock's exposure to liquidity risk. A stock's exposure to Pastor and Stambaugh's (2003) aggregate liquidity factor increases significantly during the liquidity shock and then returns to its normal level afterwards, coinciding with the initial stock price concession and subsequent price recovery.

Though we provide and favor a liquidity-based explanation for the short-run market dynamics of stock prices when the underlying firm becomes financially distressed and prone to default, we cannot completely rule out some behavioral interpretations of the phenomenon. The sudden surge in default likelihood can be loosely thought of as some form of news concerning defaults. One may interpret the concurrent drastic return drop and subsequent return reversal as investors overreact to such default news during the portfolio formation month. Given the increasingly uncertainty associated with financially distressed firms and the absence of Wall Street coverage on their stocks, investors may become overconfident about their own interpretation of the default news, and drive the price below the fundamental values (c.f. Daniel, Hirshleifer, and Subrahmanyam, 1998 and Odean, 1998). When more information about the prospectus of the firm becomes available and the uncertainty resolves, price converges back to fundamental values. In this context, some element of slow information diffusion is particularly relevant for the valuation errors of the agents (Hong and Stein, 1998). Finally, the documented clientele change in the underlying stockholder also echoes well with the heterogeneous investor assumption in Hong and Stein (1998) and valuation regime switch in Barberis, Shleifer and Vishny (1998). We believe further research relating the behavioral bias to the default news is warranted.

In this paper, we measure the default or financial distress risk using Default Likelihood Indicator (DLI) proposed by Vassalou and Xing (2004), which has the advantage of incorporating market price information that is more frequently updated. However, since DLI is estimated at monthly frequency, we still cannot identify the exact time at which a firm experiences a sharp increase in default risk. Our approach, which is essentially a calendar-time approach, only identifies the *average* impact of default risk on stock liquidity at a portfolio level. A complimentary event-time approach which focuses on large credit rating downgrades for individual firm, could potentially provide a sharper identification of such impact. In addition, if the bond of the firm is also traded, we can make use of the information embedded in the bond price change to better isolate that component of the stock price change which is due to the liquidity shock. These are potential venues for future research.

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Appendix A: Variance Decomposition of the Default Likelihood Indicator (DLI)

Empirically, the Default Likelihood Indicator is computed as a function of three variables: leverage (lev), past stock return (ret) and asset volatility (σ_A), i.e., $DLI = N\left(-DD\right) = f(lev, ret, \sigma_A)$. We want to examine the relative importance of these three variables in a variance decomposition framework. Theoretically, as normal CDF is a monotone transformation of its argument ($-DD$), we can either work with the transformed variable (DLI) or the original variable($-DD$). Unfortunately, directly working with DLI is challenging because DLI is highly skewed due to the nonlinear transformation of normal CDF. Therefore, we decide to study the variance decomposition of the equivalent variable: $-DD$, which is better-behaved statistically.

Applying the first-order Taylor series expansion of $-DD$ around the cross-sectional mean of lev, ret and σ_A, we have[47]:

$$-\overline{DD} = \frac{\partial f}{\partial lev}\overline{lev} + \frac{\partial f}{\partial ret}\overline{ret} + \frac{\partial f}{\partial \sigma}\overline{\sigma_A} + \kappa, \tag{9}$$

where κ captures the approximation error, and variables with upper bar are cross-sectionally demeaned. Therefore, we have

$$var(DD) = \frac{\partial f}{\partial lev}cov(DD, lev) + \frac{\partial f}{\partial ret}cov(DD, ret) + \frac{\partial f}{\partial \sigma}cov(DD, \sigma_A) + cov(DD, \kappa), \tag{10}$$

where $var\left(\cdot\right)$ and $cov\left(\cdot\right)$ are the cross-sectional variance and covariance, respectively. Dividing both sides of the above equation by $var(DD)$, we then have

$$1 = \frac{\partial f}{\partial lev}\beta_{lev} + \frac{\partial f}{\partial ret}\beta_{ret} + \frac{\partial f}{\partial \sigma}\beta_{\sigma_A} + \beta_{\kappa}. \tag{11}$$

The term $\frac{\partial f}{\partial(\cdot)}\beta_{(\cdot)}$ then measures the contribution of each input to the cross-sectional variations of DLI. The sum of the contribution from the three factors is less than one, and the difference, as captured by β_{κ}, is due to the approximation error in the Taylor series expansion. The partial derivatives, or sensitivity, $\frac{\partial f}{\partial(\cdot)}$ are computed numerically by the finite difference method. β can be measured by regression. For instance, β_{lev} is estimated by regressing $\overline{lev}$ on $-\overline{DD}$ cross-sectionally

[47] For simiplicity of notation, we omit the time subscript t and firm superscript i.

(so the intercept of the regression is zero by construction). Empirically, we have a panel data of $-DD$, lev, ret and σ_A. To estimate β, we follow Vuolteenaho (2002) and run a Weighted Least Squares (WLS) regression. In practice, this means deflating the data for each firm-date by the number of firms in the corresponding cross-section. The results are reported in Table 1. We report only simple WLS standard error. The simple WLS standard errors translate to t-values above fifty for all estimates; therefore, we are confident that all the estimates will still be significant, even if we adjust for auto-correlation and cross-sectional correlation of the error terms. Of course, this is hardly surprising, as (11) is merely a statement of an identity.

Appendix B: Additional Discussions

Are results driven by bid-ask spreads?

One particular problem associated with illiquid stocks traded at low prices is that the bid-ask bounce could lead to a non-negligible upward bias in average return computation, as discussed in Blume and Stambaugh (1983) and most recently in Canina, Michaely, Thaler and Womack (1998). A natural question is whether the first-month high return on the highest-DLI stock portfolio is entirely driven by the bias due to the bid-ask bounce. We believe that the answer is no.

We approach this question by estimating the impact of the bid-ask bouce 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 bid and ask price, respectively. First, assuming a bid-ask spread of \$0.25 and given an average price of \$3.58 for stocks in the highest-DLI stock portfolio, a rough estimate for the bias is 12 bps $= \left(\frac{0.25}{3.58 \times 2}\right)^2$, which is much smaller than the 90 bp return premium the highest-DLI stocks earn over the stocks in the next highest-DLI decile. Second, we also compute the bias measure for individual stock and average the bias measures first within each DLI decile and then across time. We report the average monthly return bias due to bid-ask bounce for each DLI decile in Panel A of Table XIII. For this calculation, we again assume a bid-ask spread of \$0.25, which is typically higher than the actual bid-ask spread especially for penny stocks.[48] Therefore, the return bias measures we compute are most likely overestimates and can thus serve as an upper bound for the true return bias. For example, Blume and Stambaugh (1993) choose a single day at random - Dec 13, 1973 - and select all NYSE common stocks with bid prices less than \$8. The average bias measure for these 332 stocks is only 5 bps. As expected, the bias increases with DLI. The bias is 54 bps for the highest-DLI decile, which is higher than the rough estimate of 12 bps we calculated earlier using the average price. This is because our assumption on the bid-ask spread generates extremely large bias measure on penny stocks which overstates the average. However, the difference in the average bias measure between stocks in DLI-decile 10 and stocks in DLI-decile 9 is only 26 bps, again much smaller than their return difference of 90 bps. As a robustness check, we also compute an alternative return bias measure in a subsample from 1983

[48] For a stock with a price less than or equal to \$0.25, the assumption of a \$0.25 bid-ask spread does not make much sense. We therefore assume a bid-ask spread equal to 50% of the trading price for such a stock.

to 1999, using the actual quoted spread (quoted ask – quoted bid) from quote data in TAQ and ISSM.[49] As trade could happen between the quoted bid and quoted ask, the alternative return bias measure is again likely to be overstated.[50] The alternative return bias measure is uniformly smaller than the first return bias measure. Again the difference in the average bias measure between stocks in DLI-decile 10 and stocks in DLI-decile 9 (25 bps) is much smaller than their return difference of 90 bps.

As a more direct way of accoutning for the bid-ask bouce, we 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.[51] After excluding the return on the first trading day of the calendar month, the return drops only slightly. For example, the first-month return of the highest-DLI stocks drops to 2.01% from 2.10%, indicating that the impact of bid-ask-bounce is small. To conclude, all the above evidence seems to suggest that random bounce between bid and ask does not fully explain the first-month high return on the highest-DLI stock portfolio.[52]

Insert Table XIII about here

Are results driven by increased uncertainty?

A sharp increase in a stock's DLI measure is usually associated with higher uncertainty regarding the firm's "fundamentals" at least temporarily. The increased uncertainty could lead to a higher expected stock return in the near future as in Merton (1987). Later on, as uncertainty resolves, the expected return goes back to its normal level. If such uncertainty-based explanation is true, we would expect stocks with higher level of uncertainty to have higher returns during the first

[49] The sampling period for NYSE stocks is from 1983 to 1999 and the sampling period for NASDAQ stocks is from 1987 to 1999. Because the ISSM data were constructed in early years through data collection from various sources, not all transaction records are in the database. In particular, six months worth of data for NASD stocks from 1987 through 1989 in ISSM are missing.

[50] For example, floor traders at NYSE can cross the trades by taking the opposite side of the incoming order and execute at the better of bid or ask quotes. It is also possible that large blocks can be executed on the up-stair market.

[51] We thank Nai-fu Chen for suggesting this return measure.

[52] It is possible that for stocks in the highest-DLI decile, their prices 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 will lead to a much larger first-month return on these stocks. However, such systematic bid-ask bounce is entirely consistent with our explanation. The fact that trade occurs at the bid during portfolio formation indicates large selling pressure after the stock becomes financially distressed. As more buyers come to the market in the next month, trade occurs at the ask.

month after portfolio formation. Empirically, we focus on the group of "new" high DLI stocks since they drive most of the results in the paper. We use a cash-flow based uncertainty measure developed by Zhang (2006). At the end of each month, we further sort "new" high DLI stocks into two portfolios according to the uncertainty measures and compute the equally-weighted portfolio return during the first month after portfolio formation for each portfolio separately. The first-month returns on these two portfolios turn out to be similar: 3.17% for "new" high DLI stocks with high level of uncertainty measures and 3.35% for "new" high DLI stocks with low level of uncertainty measures. The difference of 18 bps is not significant (t-value = 0.5). We therefore believe that increased uncertainty is unlikely to be the main explanation of the first-month high return on the highest-DLI stock portfolio.

Economic significance of the first-month high returns

In this paper, we focus on stocks with high DLIs. These stocks earn about 90 basis points more than otherwise similar stocks during the first month after portfolio formation. These stocks with large exposure to default risk, are more likely to have smaller market capitalizations, lower trading prices and higher percentage trading costs, as shown in Panel A of Table VII.[53] Naturally, a question arises, is the first-month high return on these stocks economically significant? In other words, can such high return be captured by portfolio trading strategies after accounting for transaction costs? This subsection answers this question in detail.

Insert Table XIV about here

We further sort these stocks into quartiles according to their market capitalizations. We then compute the average monthly returns for each quartile. We also compute the average percentage bid-ask spread and the average return bias due to bid-ask bounce for each quartile. Again, both measures are computed using the actual quoted spread (quoted ask – quoted bid) from quote data in TAQ and ISSM. The sampling periods for these two measures are from 1983 to 1999 for NYSE stocks and from 1987 to 1999 for NASDAQ stocks. This quoted spread is likely to over-estimate the true "effective" bid-ask spread. The results are presented in Panel A of Table XIV. First, for

[53] During the sampling period from 1971 to 1999, there are on average 260 stocks in the highest DLI-decile per month, with a total market capitalization slightly above 10 billion dollars (from 3 billion dollars at in 1971 to 30 billion dollars in 1999).

all four quartiles, the first-month returns after portfolio formation are much higher than the return bias measures. Therefore, random bid-ask bounce do not completely explain the high first-month returns. It is more likely that trading price, on average, systematically bounces from bid at portfolio formation to ask a month later, which is consistent with our liquidity-based explanation. Second, the first-month high returns are primarily driven by penny stocks in the lowest-size quartile. These stocks have an average market cap of 2 million dollars, an average trading price of only $1.27 and an average first-month return of 5.76%. This relatively high return is expected. Given its low price, the same bounce from bid to ask will result in a higher return. Finally, For all four quartiles, the average transaction costs as measured by the percentage bid-ask spreads are much higher than the first-month returns, which means that the first-month high return on high-DLI stocks is, on average, economically insignificant. Our liquidity-based explanation would predict a more pronounced price reversal for the subsample of high-DLI stocks that have recently experienced increases in DLIs. When we examine the New DLI stocks, which enter the highest-DLI decile only during the portfolio formation month, we observe larger (in absolute term) negative returns during the portfolio formation month and higher positive returns in the month after. However, these high returns are still not economically significant since they are on average smaller than the transaction costs. Similar results are obtained when we sort high-DLI stocks into quartiles according to their trading prices at portfolio formation as in Panel B of Table XIV. In conclusion, outside investors (other than the market makers) cannot consistently capture the first-month high returns on high-DLI stocks by trading at monthly frequency. This is consistent with the findings in Avramov, Chordia and Goyal (2005) in which they show the profits to contrarian trading strategy are smaller than the likely transaction costs and therefore short-term return reversal does not constitute a violation of efficient market hypothesis. Finally, this is also consistent with the view that market makers, generically defined, are compensated by providing liquidity when it is most needed.

Compensation for liquidity provision during the later sub-sample

Liquidity of the stock market improves significantly since July, 1997 due to various institutional changes on the exchanges. The new Order Handling Rules (OHR) was phrased-in during early 1997 for all NASDAQ stocks, which allows the general public to compete more effectively with NASDAQ market makers in liquidity provision via limit orders. In addition, tick size was cut down from $1/8 to \$1/16 for both NYSE and NASDAQ stocks on June of 1997. If part of the higher return on High-DLI stocks is indeed a compensation for liquidity provision, we would expect it to decrease after June 1997.[54] The sub-sample result during the later period from July 1997 to the end of 1999 confirms this observation. The Fama-French three-factor risk-adjusted return on the highest-DLI stock portfolios is only 6 bps on average during this period and is not statistically significant.

Market Maker's Inventory

Our liquidity provision explanation would predict a temporary increase in market maker's inventory when a stock recently becomes finally distressed. Due to data limitation, we cannot directly test the market maker's inventory changes. An indirect (albeit imperfect) measure is the stock-level aggregate order imbalances, which capture market making and inventory by traders other than the specialists as well as the specialists, and should be related to the specialists' end-of-day inventory position (at least for NYSE traded stocks). Results from the order imbalance diagnostics (see Panel C of Table XI) suggest that market maker on average take large long positions in the new high DLI stocks, and provide liquidity to the markets. This interpretation is reinforced by findings in Hendershott and Seasholes (2006). Using actual NYSE specialist data, they show the NYSE specialists' inventory positions are negatively correlated with past returns, and large increase in inventory is negatively related to future returns (see Figure 4 in their paper).

[54] We thank Joel Hasbrock and Larry Glosten for pointing this out.

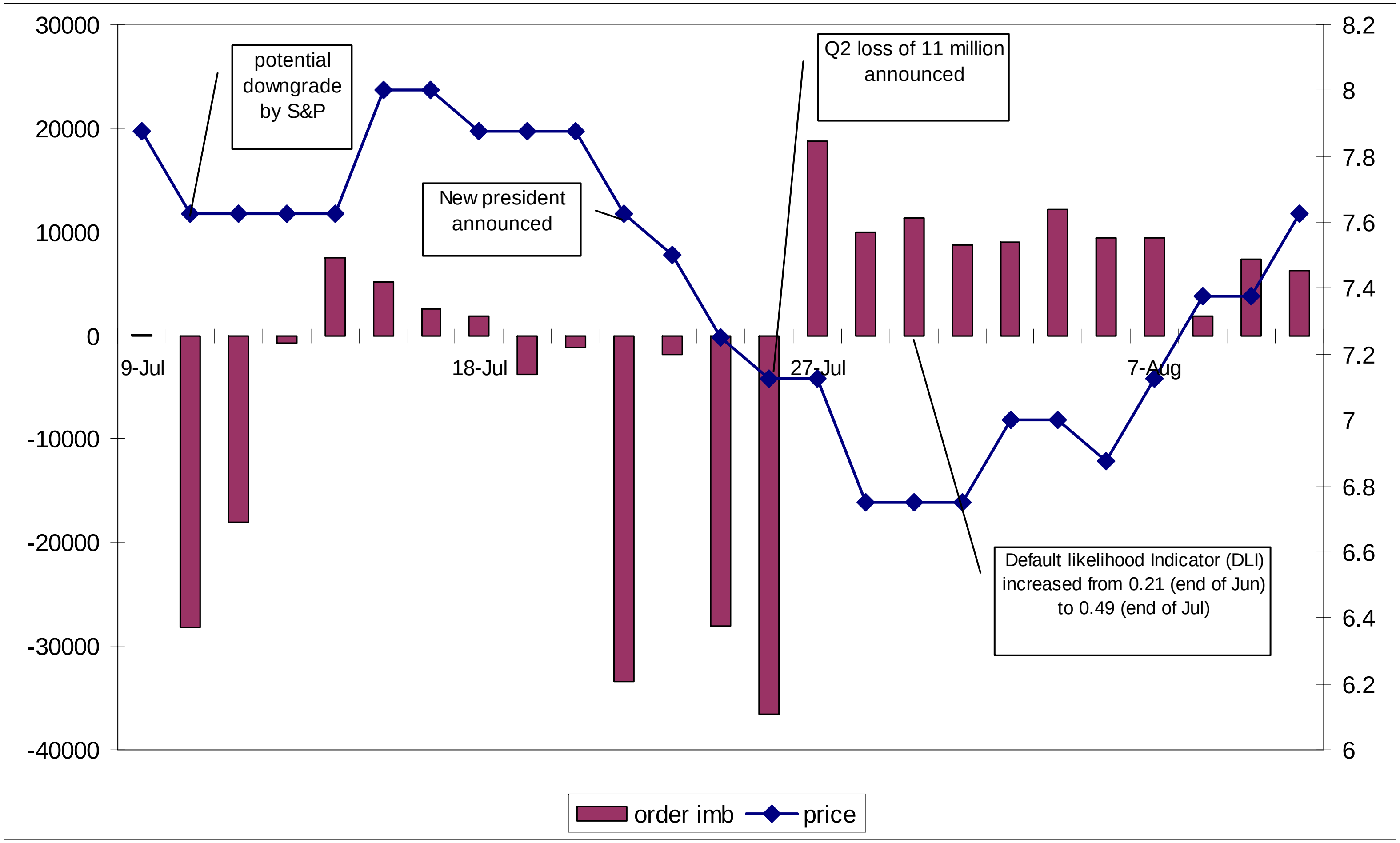

Figure 1: This figure plots the daily closing price (in blue line) and daily order imbalance (number of buyer-initiated shares purchased less than the seller-initiated shares sold, in red bar) for Midway Airlines (ticker = MDW) during the period from Jul 9 to Aug 10, 1990.

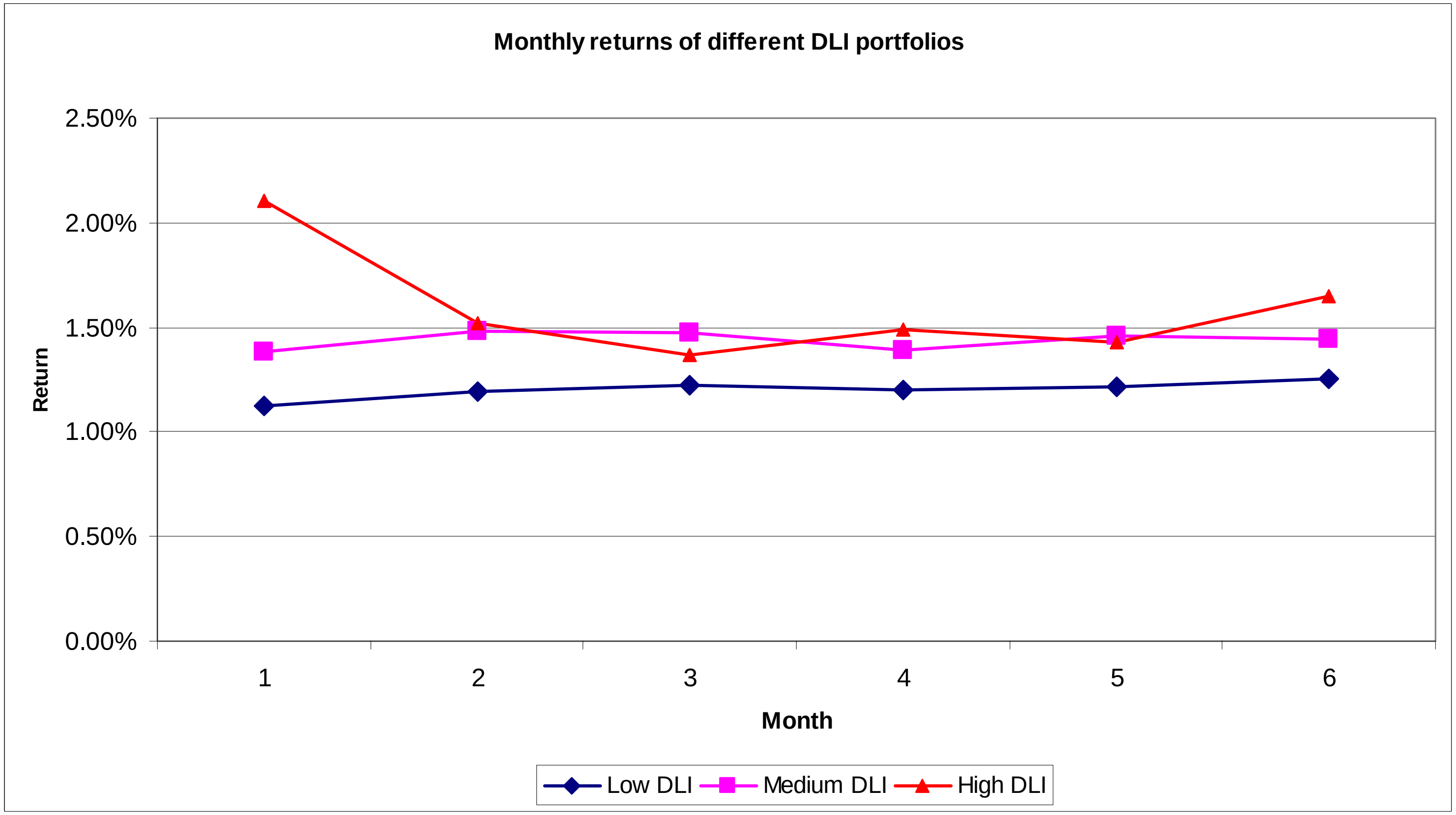

Figure 2: This figure plots the average equally-weighted returns during portfolio formation month and each of the first six months after portfolio formation for stocks in the highest, the lowest and medium DLI deciles. The sampling period is from 1971/01 to 1999/12.

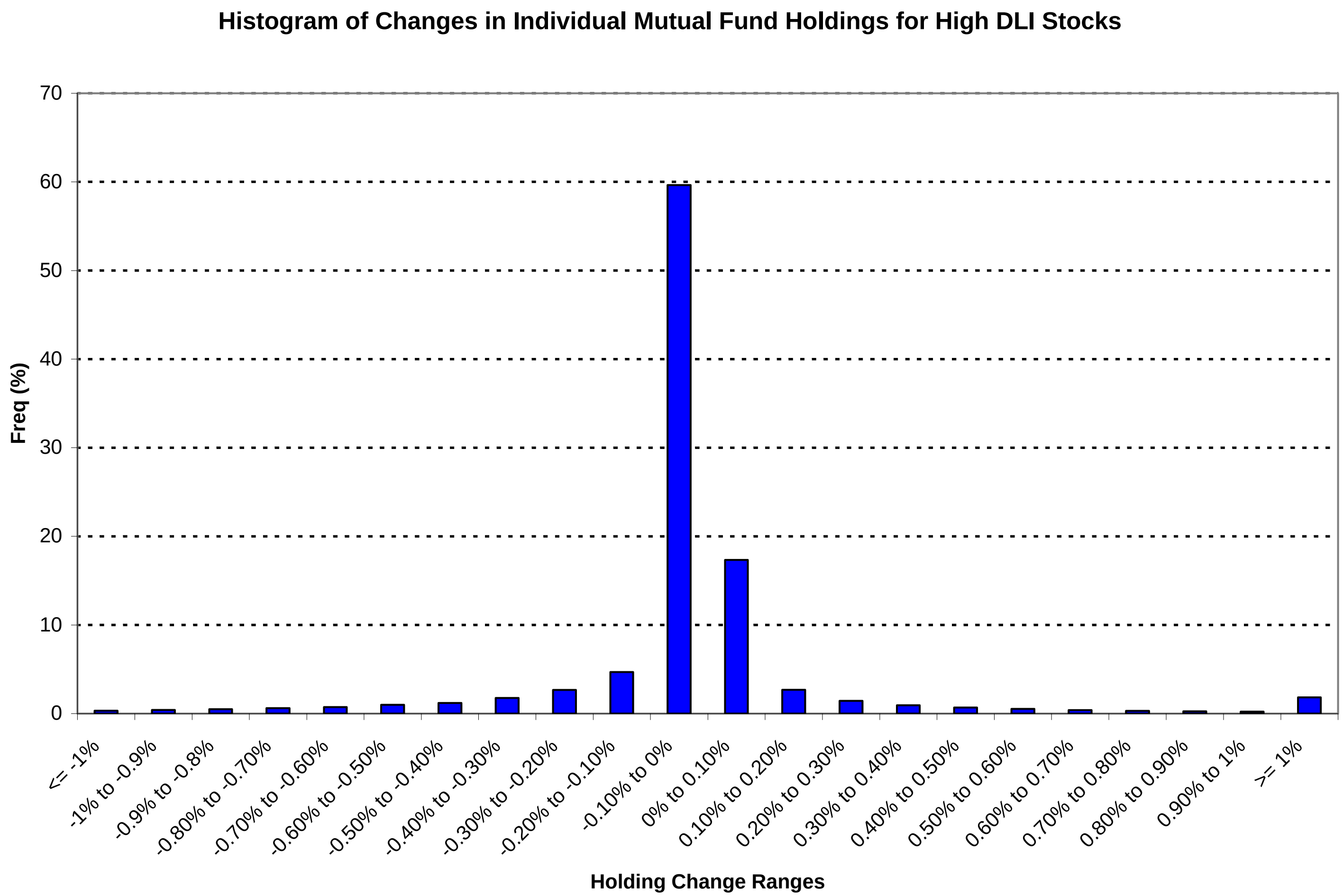

Figure 3: This figure plots the histogram of changes in individual mutual fund holdings for high DLI stocks. The sampling period is from 1980/01 to 1999/12.

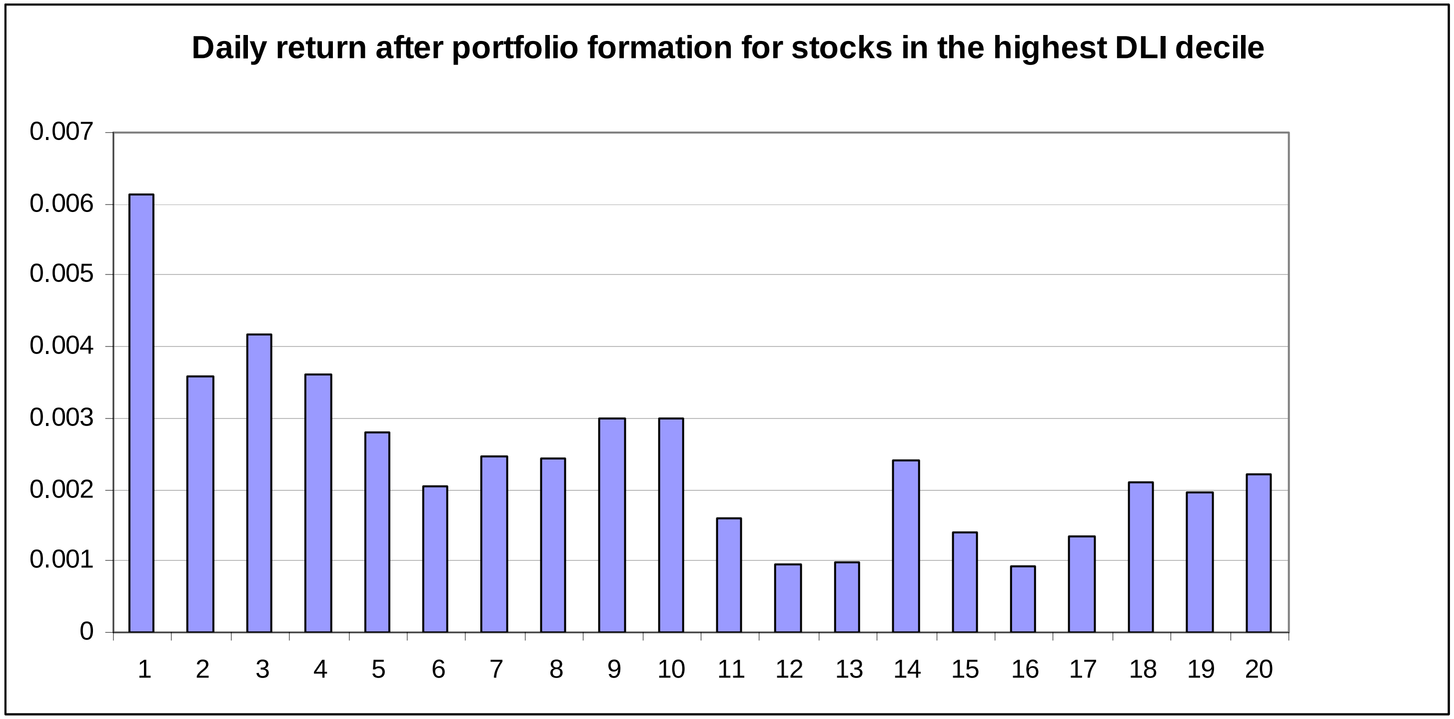

Figure 4: This figure plots the average equally-weighted daily returns during each of the first 20 days after portfolio formation for stocks in the highest DLI decile. The sampling period is from 1971/01 to 1999/12.

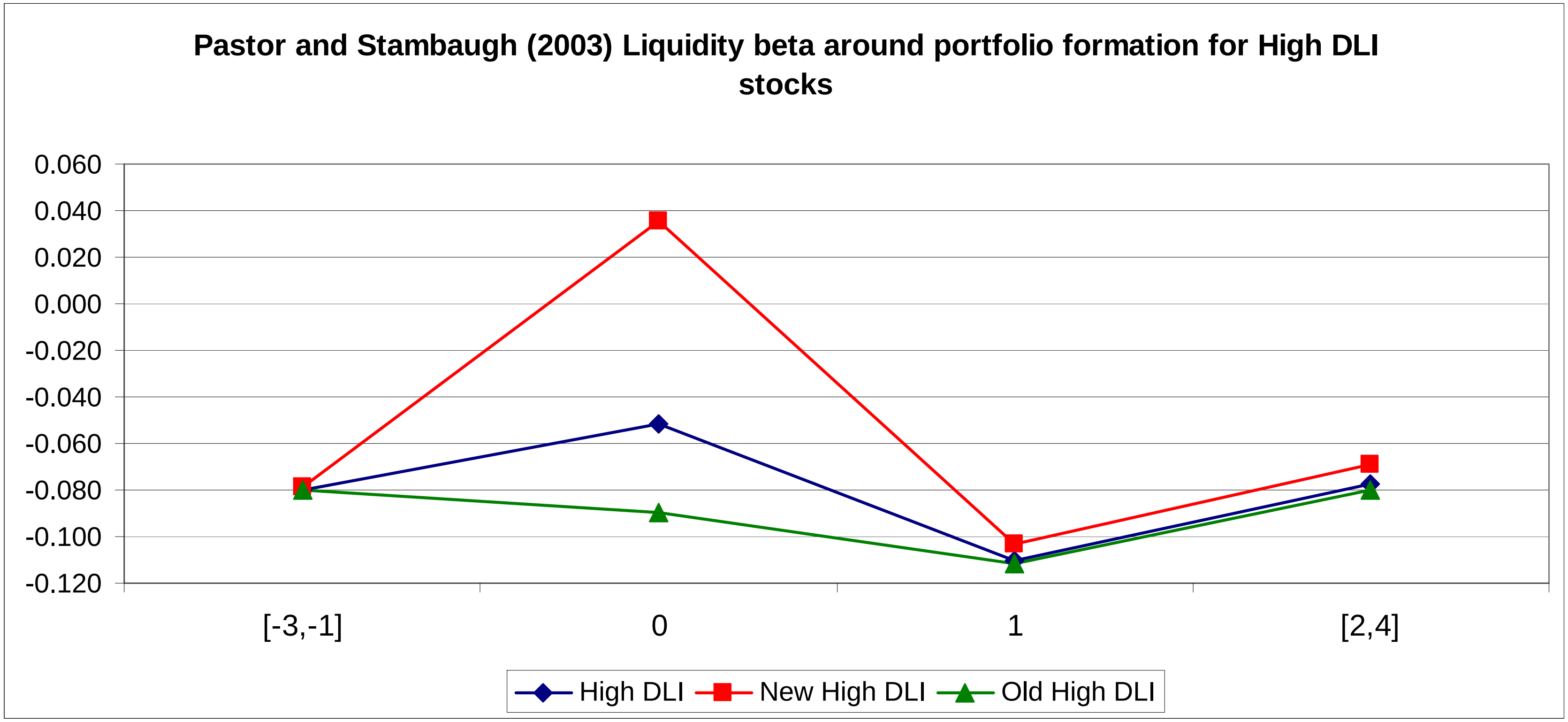

Figure 5: This figure plots the liquidity betas around the portfolio formation for High DLI stocks (stocks in the highest-DLI decile), New High DLI stocks (subset of High DLI stocks that do not belong to the highest-DLI decile in the previous month) and Old High DLI stocks (the remaining High DLI stocks that also belong to the highest-DLI decile in the previous month). "[-3,-1]" refers to the three months prior to the portfolio formation month; "0" refers to the the portfolio formation month; "1" refers to the first month after the portfolio formation month and "[2,4]" refers to the second to fourth month after portfolio formation. The sampling period is from 1971/01 to 1999/12

Table I: Delisting probabilities broken down by horizon, since portfolio formation month, sorted on DLI

The following table reports the delisting probabilities (in percentage) broken down by horizon, since portfolio formation month, where all stocks are sorted into deciles based on the value of default likelihood indicator (DLI). All the numbers are reported in percentage. Panel A reports the total delisting probabilities; Panel B reports the probabilities of delisting due to performance-related reasons (CRSP delisting code between 400 and 599). The sampling period is from Jan 1971 to Dec 1999.

Panel A: Total delisting probability

Month	Delisted in 1st Month	Delisted in 2nd Month	Delisted in 3rd Month	Delisted in 4th Month	Delisted in 5th Month	Delisted in 6th Month	Delisted in 7-12 Month	Total prob in the 1st year
Low DLI	0.27	0.28	0.31	0.29	0.28	0.31	1.91	3.38
2	0.35	0.36	0.36	0.34	0.36	0.33	2.21	3.96
3	0.44	0.43	0.42	0.44	0.41	0.41	2.54	4.65
4	0.48	0.49	0.48	0.47	0.52	0.49	2.81	5.26
5	0.53	0.56	0.56	0.54	0.5	0.5	3.13	5.79
6	0.57	0.56	0.52	0.55	0.55	0.57	3.2	5.95
7	0.51	0.53	0.53	0.56	0.56	0.54	3.44	6.16
8	0.48	0.51	0.53	0.55	0.55	0.58	3.81	6.53
9	0.49	0.52	0.62	0.63	0.69	0.74	4.58	7.78
High DLI	1.48	1.5	1.48	1.51	1.47	1.43	7.53	14.92

Panel B: Delisting probability due to performance-related reasons

Month	Delisted in 1st Month	Delisted in 2nd Month	Delisted in 3rd Month	Delisted in 4th Month	Delisted in 5th Month	Delisted in 6th Month	Delisted in 7-12 Month	Total prob in the 1st year
Low DLI	0.04	0.04	0.04	0.04	0.03	0.04	0.23	0.42
2	0.04	0.03	0.04	0.04	0.04	0.04	0.27	0.46
3	0.03	0.04	0.03	0.04	0.04	0.04	0.36	0.55
4	0.04	0.05	0.06	0.05	0.07	0.06	0.46	0.75
5	0.06	0.06	0.06	0.06	0.06	0.08	0.58	0.9
6	0.07	0.07	0.07	0.09	0.09	0.12	0.66	1.1
7	0.09	0.09	0.12	0.15	0.15	0.14	0.98	1.63
8	0.13	0.16	0.18	0.2	0.21	0.23	1.55	2.53
9	0.29	0.32	0.37	0.35	0.4	0.4	2.57	4.41
High DLI	1.33	1.32	1.29	1.29	1.23	1.18	5.93	12.24

Table II: Returns of portfolios sorted on DLI

For each month from 1971/01 to 1999/12, we sort all stocks into 10 deciles according to their DLIs. Panel A reports the equally-weighted returns of these portfolios during each of the first six months after portfolio formation. Panel B reports the average size, book-to-market ratio and DLI at the end of the first month after portfolio formation and the changes in these characteristics from the previous month.

Panel A: first six month return of the DLI-sorted portfolios

Port ID	Return (1 mth)	Return (2 mth)	Return (3 mth)	Return (4 mth)	Return (5 mth)	Return (6 mth)
Low DLI	0.0113	0.0120	0.0122	0.0120	0.0121	0.0125
2	0.0107	0.0154	0.0158	0.0164	0.0156	0.0152
3	0.0138	0.0148	0.0148	0.0139	0.0125	0.0139
4	0.0133	0.0143	0.0143	0.0145	0.0139	0.0138
5	0.0138	0.0148	0.0148	0.0139	0.0146	0.0144
6	0.0140	0.0155	0.0145	0.0142	0.0138	0.0128
7	0.0123	0.0132	0.0142	0.0137	0.0130	0.0137
8	0.0126	0.0137	0.0133	0.0131	0.0142	0.0141
9	0.0118	0.0123	0.0131	0.0131	0.0146	0.0146
High DLI	0.0210	0.0152	0.0137	0.0149	0.0143	0.0165

Panel B: Characteristics of the DLI-sorted portfolios

Port ID	MktCap ($million) 1 mth	ΔMktCap ($million)	B/M 1 mth	ΔB/M	DLI (%) 1 mth	ΔDLI (%)
Low DLI	2189.97	25.05	0.62	0.00	0.01	0.01
2	1328.26	24.47	0.73	0.01	0.02	0.02
3	941.52	14.68	0.75	0.00	0.03	0.03
4	653.11	8.47	0.79	0.01	0.07	0.06
5	459.87	7.08	0.83	0.00	0.16	0.12
6	343.50	4.28	0.90	0.01	0.41	0.24
7	229.26	3.40	0.99	0.01	1.05	0.43
8	143.43	2.17	1.13	0.01	2.85	0.70
9	81.87	1.14	1.33	0.01	8.60	0.75
High DLI	40.67	1.07	1.89	-0.03	34.89	-1.55

Table III: Two-stage optimal GMM estimation of asset pricing models using both first- and second- month returns

The tests are performed on two sets of portfolio returns during the first- and second-month after portfolio formation. Panel A presents the results using the equally-weighted monthly returns on 10-DLI sorted portfolios. Panel B represents the results using the equally weighted monthly returns on 27 portfolios sorted on size, book to market equity and DLI. MKT refers to the gross returns on the stock market portfolio. dSV is the 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 (size) stocks and short on big size stocks. The GMM estimations use Hansen's (1982) optimal weighting matrix. J-stat denotes Hansen's test on the over-identification restrictions of the model. The estimation period is from 1971/01 to 1999/12. The t-values are reported below the coefficients in *italics*.

Panel A: 10-DLI sorted portfolios

First-month returns						Second-month returns					
constant	MKT	SMB	HML	dSV	J-stat	constant	MKT	SMB	HML	dSV	J-stat
0.85	13.43	-17.02	24.75		49.77	0.88	8.77	-11.47	19.15		14.76
10.31	*1.72*	*-2.38*	*2.38*		*0.00*	*14.69*	*1.65*	*-2.18*	*2.34*		*0.02*
0.81	12.00	21.17	38.43	-132.17	8.38	0.84	12.44	-6.50	25.18	-33.12	7.63
6.79	*1.28*	*1.56*	*2.90*	*-3.08*	*0.14*	*10.26*	*1.77*	*-0.86*	*2.36*	*-1.11*	*0.18*

Panel B: 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
1.00	0.82	0.53	-5.13		163.05	0.98	1.77	-1.32	-3.42		113.12
44.31	*0.41*	*0.23*	*-1.86*		*0.00*	*46.22*	*0.85*	*-0.58*	*-1.23*		*0.00*
0.93	4.88	7.85	-5.21	-39.44	133.69	0.95	4.55	3.29	-2.02	-25.98	111.37
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 IV: Characteristics during and after portfolio formation

For each of the 27 equally weighted portfolios sorted on size, book-to-market ratio (B/M) and DLI, we report the average size, B/M and DLI at the end of the portfolio formation month and one month after. The estimation period is from 1971/01 to 1999/12.

Portfolio			Size ($million)		B/M		DLI (%)	
Size	B/M	DLI	Portfolio formation month	One month after	Portfolio formation month	One month after	Portfolio formation month	One month after
Small	High	High	12.53	12.74	2.03	2.00	16.64	16.46
Small	High	Medium	17.05	17.31	1.54	1.54	0.17	0.38
Small	High	Low	18.59	18.78	1.50	1.49	0.00	0.01
Small	Medium	High	14.44	14.62	0.82	0.83	9.65	9.98
Small	Medium	Medium	19.73	19.99	0.81	0.82	0.13	0.27
Small	Medium	Low	21.04	21.26	0.81	0.81	0.00	0.03
Small	Low	High	13.98	14.21	0.36	0.38	10.32	10.80
Small	Low	Medium	20.04	20.48	0.39	0.40	0.11	0.26
Small	Low	Low	22.37	22.74	0.39	0.40	0.00	0.03
Medium	High	High	88.70	89.67	1.72	1.72	9.64	9.73
Medium	High	Medium	97.11	98.39	1.38	1.38	0.14	0.31
Medium	High	Low	99.87	100.90	1.29	1.29	0.00	0.02
Medium	Medium	High	95.32	96.28	0.81	0.82	5.16	5.38
Medium	Medium	Medium	106.84	108.20	0.80	0.80	0.11	0.24
Medium	Medium	Low	120.28	121.38	0.79	0.79	0.00	0.01
Medium	Low	High	97.81	99.27	0.39	0.40	4.96	5.24
Medium	Low	Medium	107.58	109.56	0.39	0.40	0.10	0.24
Medium	Low	Low	124.06	126.01	0.39	0.40	0.00	0.02
Big	High	High	1111.65	1126.22	1.56	1.55	7.87	7.77
Big	High	Medium	1570.78	1589.43	1.32	1.32	0.11	0.26
Big	High	Low	1755.62	1766.38	1.25	1.24	0.00	0.03
Big	Medium	High	1159.58	1178.61	0.80	0.81	5.08	5.18
Big	Medium	Medium	1692.97	1711.36	0.79	0.79	0.10	0.22
Big	Medium	Low	2371.23	2387.20	0.77	0.77	0.00	0.01
Big	Low	High	1544.19	1557.13	0.39	0.41	3.94	4.01
Big	Low	Medium	2010.20	2037.37	0.40	0.40	0.09	0.21
Big	Low	Low	4456.93	4515.04	0.36	0.37	0.00	0.01

Table V: Default factor loadings during the first and the second month after portfolio formation

We report the factor loadings on the aggregate default risk factor (*dSV*) for both 10 DLI-sorted portfolios and 27 portfolios sorted on size, book to market and DLI, during the first and the second month after portfolio formation. The estimation period is from 1971/01 to 1999/12.

Panel A: Default factor betas for the 10-DLI sorted portfolios

Portfolio	Low DLI	2	3	4	5	6	7	8	9	High DLI
1st month	-0.056	-0.029	-0.056	0.104	0.201	0.330	0.278	0.357	0.976	1.904
2nd month	-0.015	-0.149	0.004	0.123	0.180	0.284	0.378	0.335	0.996	1.804

Panel B: Default factor betas for the 27 size / book-to-market / DLI sorted portfolios

Size	B/M	DLI	1st month	2nd month
Small	High	High	1.578	1.510
Small	High	Medium	0.806	0.847
Small	High	Low	0.127	0.286
Small	Medium	High	0.888	0.762
Small	Medium	Medium	0.515	0.635
Small	Medium	Low	0.598	0.458
Small	Low	High	0.787	1.002
Small	Low	Medium	0.566	0.429
Small	Low	Low	0.509	0.768
Medium	High	High	0.639	0.636
Medium	High	Medium	0.303	0.353
Medium	High	Low	0.473	0.275
Medium	Medium	High	0.526	0.428
Medium	Medium	Medium	0.155	0.063
Medium	Medium	Low	0.154	0.159
Medium	Low	High	0.136	0.543
Medium	Low	Medium	-0.142	-0.029
Medium	Low	Low	-0.091	-0.120
Big	High	High	0.623	0.416
Big	High	Medium	-0.017	0.165
Big	High	Low	-0.021	0.160
Big	Medium	High	-0.193	-0.076
Big	Medium	Medium	0.073	0.103
Big	Medium	Low	0.000	-0.012
Big	Low	High	0.352	0.188
Big	Low	Medium	-0.228	-0.219
Big	Low	Low	-0.202	-0.190

Table VI: Variance decomposition of Default Likelihood Indicator (DLI) based on leverage, past-return and asset volatility

This table reports the percentage of total cross-sectional variation in DLI explained by financial leverage, past one-year return and asset volatility in a variance decomposition framework. We have preformed the decomposition on the full sample (Panel A), the top 1/3 of the sample with the highest DLI (Panel B) and the top 1/5 of the samples with the highest DLI (Panel C). The sampling period is from 1971/01 and 1999/12. Details are provided in the Appendix.

	Leverage	Past One-year Return	Asset Volatility	Approximation Errors
Panel A: Full Sample				
Average	0.69	0.02	0.56	
Sensitivity of -DD	1.54	-1.79	3.44	
Beta with respect to -DD	0.34	-0.10	0.06	
WLS Standard Errors	0.00	0.00	0.00	
Percentage of Variance Explained	51.82%	17.03%	20.23%	10.92%
Panel B: top 1/3 DLI sample				
Average	1.47	-0.20	0.74	
Sensitivity of -DD	0.37	-1.35	1.09	
Beta with respect to -DD	1.39	-0.24	0.07	
WLS Standard Errors	0.01	0.00	0.00	
Percentage of Variance Explained	51.70%	31.76%	7.13%	9.41%
Panel C: top 1/5 DLI sample				
Average	2.01	-0.34	0.80	
Sensitivity of -DD	0.21	-1.26	0.60	
Beta with respect to -DD	2.34	-0.27	0.06	
WLS Standard Errors	0.02	0.00	0.00	
Percentage of Variance Explained	48.70%	34.26%	3.69%	13.35%

Table VII: 10 DLI-sorted portfolios, their migration matrix and the associated returns during portfolio formation month and the first-month after portfolio formation

At the end of each month from 1970/12 to 1999/12, we sort all stocks into 10 deciles according to their DLIs (decile 1: Low DLI and decile 10: High DLI). Panel A reports the equally-weighted return during and one month after portfolio formation, and various characteristics of these portfolios. The Amihud illiquidity measures are multiplied by 1000. The average analyst coverage is estimated from 1984/01 to 1999/12.

Panel B reports the transition probability of a stock moving from DLI decile i during the month immediately prior to the portfolio formation month (t-1) to DLI decile j during the portfolio formation month (t). Panel C and D report the associated equally-weighted returns during the portfolio formation month (t) and one month after portfolio formation month (t+1), respectively. Panel E reports the corresponding Fama-French three-factor risk-adjusted returns during the first month after portfolio formation (t+1). Risk-adjusted-returns that are statistically significant (at 5% confidence level) are highlighted in bold. The sampling period is from 1970 to 1999.

Panel A:

Port ID	Return one month after formation	Return during formation month	Characteristics (mean)							
			DLI (%)	MktCap (in million)	Book-to-market	Price	Amihud	Idio risk	% of analyst coverge	# of analyst
Low DLI	0.0113	0.0248	0.00	2164.92	0.62	52.12	0.47	86.3%	73.5%	5.39
2	0.0107	0.0231	0.00	1303.78	0.73	29.37	0.92	86.5%	76.7%	4.98
3	0.0138	0.0270	0.00	926.84	0.75	24.48	0.87	88.2%	67.4%	4.55
4	0.0133	0.0268	0.01	644.64	0.78	20.06	1.29	89.0%	62.6%	4.20
5	0.0138	0.0240	0.04	452.80	0.83	17.02	1.56	89.9%	57.0%	3.80
6	0.0140	0.0208	0.17	339.21	0.89	14.52	2.51	90.8%	51.7%	3.42
7	0.0123	0.0167	0.61	225.86	0.99	11.51	3.52	91.9%	44.9%	3.11
8	0.0126	0.0086	2.15	141.27	1.12	8.77	6.24	93.3%	36.6%	2.87
9	0.0118	-0.0022	7.85	80.72	1.32	6.12	11.54	94.8%	29.1%	2.60
High DLI	0.0210	-0.0339	36.45	39.60	1.92	3.58	31.75	96.6%	20.3%	2.50

Decile # at t-1	Decile # at t									
	1	2	3	4	5	6	7	8	9	10
Panel B: Transition probability from month t-1 to t (in %)										
1	81.68	7.20	6.63	2.14	0.95	0.63	0.42	0.23	0.10	0.02
2	20.36	50.55	19.93	5.18	1.86	1.05	0.55	0.33	0.16	0.02
3	13.71	11.06	42.29	21.93	6.78	2.36	1.08	0.52	0.22	0.05
4	3.68	2.60	21.85	39.69	21.74	6.77	2.31	0.96	0.34	0.07
5	1.41	0.83	6.36	23.29	37.96	21.11	6.41	1.95	0.56	0.12
6	0.68	0.33	1.96	7.17	22.88	38.70	21.08	5.67	1.33	0.20
7	0.34	0.17	0.63	1.91	6.63	22.85	41.26	21.43	4.31	0.46
8	0.12	0.09	0.26	0.54	1.58	5.68	22.61	46.95	20.52	1.65
9	0.07	0.04	0.07	0.15	0.36	1.02	4.06	20.60	57.81	15.83
10	0.02	0.01	0.02	0.03	0.05	0.14	0.37	1.57	15.09	82.70
Panel C: Average monthly return during month t (in %)										
1	1.75	-1.83	-2.38	-2.69	-2.74	-2.27	-2.91	-4.93	-4.23	-6.57
2	5.06	1.63	-1.85	-4.32	-5.26	-3.63	-5.15	-5.94	-8.90	-6.24
3	6.37	5.21	1.83	-1.89	-4.22	-4.58	-4.35	-6.33	-9.21	-11.88
4	6.55	7.99	5.98	1.69	-2.69	-5.29	-5.86	-6.38	-12.09	-18.51
5	5.30	8.24	8.88	6.51	1.37	-3.57	-6.39	-8.85	-12.11	-21.01
6	5.87	6.72	9.15	10.48	7.18	1.03	-4.57	-8.53	-12.53	-15.67
7	7.04	5.51	9.21	12.02	12.60	7.81	0.58	-6.26	-12.87	-21.01
8	6.84	7.08	6.03	12.29	15.44	16.01	9.06	0.16	-8.67	-19.50
9	3.84	5.00	6.19	10.87	18.02	20.23	20.42	11.40	-0.38	-12.70
10	2.10	7.73	4.31	7.00	8.72	14.46	33.00	35.95	16.86	-1.18
Panel D: Average monthly return during month t+1 (in %)										
1	1.09	1.21	1.51	1.71	1.39	1.82	1.47	3.37	1.33	0.69
2	1.16	1.07	1.58	1.13	1.48	3.79	0.36	2.98	4.21	3.99
3	1.34	1.00	1.47	1.45	1.34	2.02	1.51	3.09	0.22	5.68
4	0.96	1.12	1.23	1.26	1.52	1.67	1.81	3.76	2.05	4.37
5	1.77	-0.75	1.24	1.22	1.35	1.66	2.15	1.94	3.74	1.64
6	1.34	1.00	0.96	1.02	1.33	1.37	1.69	2.14	2.62	2.19
7	1.26	0.85	-0.07	1.17	1.34	1.22	1.20	1.53	2.23	2.14
8	0.95	0.53	3.08	2.04	1.02	0.48	0.77	1.32	1.98	2.00
9	-0.36	2.85	0.50	2.92	-0.15	0.88	-0.15	0.40	1.13	3.03
10	-5.81	-4.60	-1.29	4.21	1.25	2.78	0.01	0.37	-0.31	1.93
Panel E: Average three-factor risk-adjusted monthly return during month t+1 (in %)										
1	0.06	0.25	0.42	0.93	0.49	0.75	0.62	2.17	0.26	2.27
2	-0.08	-0.17	0.27	-0.29	-0.12	1.76	-0.34	2.00	-0.54	10.01
3	0.43	-0.05	0.35	0.34	0.10	1.03	0.37	2.32	-0.39	1.58
4	0.12	0.19	0.12	0.13	0.30	0.46	0.55	1.48	0.93	3.08
5	0.78	-1.61	0.14	0.04	0.19	0.36	0.81	0.48	2.46	-0.60
6	0.36	-0.05	-0.20	-0.14	0.13	0.17	0.43	0.75	0.98	0.83
7	-0.17	0.26	-0.70	-0.15	0.25	-0.02	-0.12	0.23	0.69	1.60
8	0.69	0.43	1.33	1.11	-0.55	-0.74	-0.50	-0.04	**0.63**	0.42
9	-0.74	2.56	-0.17	2.05	-0.92	-0.46	-1.35	**-0.90**	-0.30	**1.37**
10	-6.61	-0.04	-0.48	-0.47	0.97	1.17	-0.71	-1.19	**-1.67**	0.35

Table VIII: Examples of investment restrictions on institutions

Institutions	Restrictions	Keywords
San Francisco State University Foundation	"Equity investment should have adequate liquidity and a market capitalization of at least $500 million."	Liquidity, Market Capitalization
The Mayer Fund	"no company in which we invest shall have a market capitalization less than $100 million; and at least three Wall Street analysts must cover the stock."	Market Capitalization, Wall street coverage
Kingsville foundation	"investments shall be primarily in well-seasoned, quality companies whose securities enjoy marketability adequate for the portfolio, Industry and company investments shall be based upon demonstrable analysis of prospects for above average return over a three-year period."	Quality of the company, above-average return
Florida College Investment Plan	"a coefficient of determination to the benchmark Index of not less than .80 over any rolling five-year time horizon calculated using monthly data."	Tracking error
University of Wisconsin System trust fund	"portfolio positions should be issues that are publicly traded in sufficient volume to facilitate, under most market conditions, prompt sale without severe market price effect."	Easiness of trading

Table IX: Aggregate mutual fund holdings and mutual fund holding changes of all and recent High-DLI stocks

This table illustrates the quarterly aggregate mutual fund holding and holding changes of all high DLI stocks and recent high DLI stocks. Panel A examines the aggregate mutual fund holdings and holding changes of all high DLI stocks when they become financially distressed during any month of the quarter. Panel B examines the aggregate mutual fund holdings and holding changes of recent high DLI stocks when they become financially distressed during any month of the quarter. Panel C reports the quarterly mutual fund holding changes during the four quarters after the event quarter (Q) for all high DLI stocks. Panel C reports the quarterly mutual fund holding changes during the four quarters after the event quarter (Q) for all recent high DLI stocks. All high DLI or recent high DLI stocks are further sorted into three groups based on the number of underlying mutual fund shareholders. "Low" refers to ones for which the underlying shareholders is less than or equal to 2, "Medium" refers to ones for which the underlying shareholders between 3 and 7 (inclusive), and "High" refers to ones for which the underlying shareholders greater than or equal to 8. The ranking approximately matches the 33rd percentile and 67th percentile of underlying mutual fund shareholders across all stocks and all years. "All" refers to the full sample irrespective of the number of the underlying mutual fund shareholders. N is the number of stocks across all quarters. The sampling period is from 1980-1999. All holdings and holding changes are reported in percentage.

Panel A: Aggregate mutual fund holdings and mutual fund holding changes of *all* High-DLI stocks

	Statistics	Aggregate Mutual Fund Holdings at (Q-1) (%)	Aggregate Mutual Fund Holdings at (Q) (%)	Quarterly Holding Changes (%)	Aggregate Mutual Fund Holdings at (Q-1) (%)	Aggregate Mutual Fund Holdings at (Q) (%)	Quarterly Holding Changes (%)	Aggregate Mutual Fund Holdings at (Q-1) (%)	Aggregate Mutual Fund Holdings at (Q) (%)	Quarterly Holding Changes (%)
		1980 - 1999			1980-1989			1990 - 1999		
Low	Mean	1.599	1.458	-0.141	1.883	1.74	-0.143	1.326	1.188	-0.139
	t-statistics	61.40	60.25	-5.53	50.86	49.77	-4.07	36.92	36.26	-3.77
	N	5711	5711	5711	2798	2798	2798	2913	2913	2913
Medium	Mean	3.707	2.641	-1.066	4.182	3.136	-1.047	3.452	2.376	-1.076
	t-statistics	75.34	69.44	-22.95	55.48	49.91	-15.00	54.47	50.53	-17.71
	N	4496	4496	4496	1570	1570	1570	2926	2926	2926
High	Mean	5.921	4.055	-1.866	5.052	4.236	-0.816	6.192	3.998	-2.194
	t-statistics	44.71	52.19	-14.92	25.58	29.95	-4.83	38.38	43.53	-14.28
	N	1033	1033	1033	246	246	246	787	787	787
All	Mean	2.839	2.17	-0.669	2.834	2.348	-0.486	2.843	2.046	-0.797
	t-statistics	95.48	97.69	-25.78	71.26	70.84	-14.42	67.43	68.91	-21.43
	N	11240	11240	11240	4614	4614	4614	6626	6626	6626

Panel B: Aggregate mutual fund holdings and mutual fund holding changes of *recent* High-DLI Stocks

	Statistics	Aggregate Mutual Fund Holdings at (Q-1) (%)	Aggregate Mutual Fund Holdings at (Q) (%)	Quarterly Holding Changes (%)	Aggregate Mutual Fund Holdings at (Q-1) (%)	Aggregate Mutual Fund Holdings at (Q) (%)	Quarterly Holding Changes (%)	Aggregate Mutual Fund Holdings at (Q-1) (%)	Aggregate Mutual Fund Holdings at (Q) (%)	Quarterly Holding Changes (%)
		1980 - 1999			1980 - 1989			1990 - 1999		
Low	Mean	1.676	1.595	-0.081	1.963	1.857	-0.107	1.351	1.299	-0.053
	t-statistics	31.37	29.64	-1.46	28.14	24.76	-1.46	16.86	17.21	-0.62
	N	1308	1308	1308	694	694	694	614	614	614
Medium	Mean	4.391	3.228	-1.163	4.659	3.719	-0.941	4.228	2.93	-1.298
	t-statistics	45.33	43.62	-12.96	33.74	31.20	-7.13	32.30	31.51	-10.84
	N	1416	1416	1416	534	534	534	882	882	882
High	Mean	7.463	5.099	-2.364	5.789	4.858	-0.931	7.994	5.175	-2.818
	t-statistics	35.75	46.79	-12.42	20.54	23.28	-4.24	31.35	40.67	-11.90
	N	586	586	586	141	141	141	445	445	445
All	Mean	3.862	2.914	-0.948	3.409	2.892	-0.517	4.181	2.929	-1.252
	t-statistics	55.59	60.74	-16.52	41.86	41.13	-7.58	40.59	45.01	-14.81
	N	3310	3310	3310	1369	1369	1369	1941	1941	1941

Panel C: Aggregate mutual fund quarterly holding change after event quarter for *all* High-DLI stocks

		Quarterly Holding Changes (Q+1 - Q) (%)	Quarterly Holding Changes (Q+2 – Q+1) (%)	Quarterly Holding Changes (Q+3 – Q+2) (%)	Quarterly Holding Changes (Q+4 – Q+3) (%)
	Mean	0.048	0.053	-0.031	0.082
Low	*t*-statistics	2.00	2.24	-1.27	3.08
	N	4326	3530	3324	3118
	Mean	-0.03	-0.233	0.034	-0.054
Medium	*t*-statistics	-0.81	-6.27	0.88	-1.38
	N	3893	3450	3209	3030
	Mean	-0.398	-0.205	0.009	0.05
High	*t*-statistics	-5.18	-2.77	0.12	0.65
	N	974	921	877	834
	Mean	-0.032	-0.102	0.002	0.019
All	*t*-statistics	-1.54	-4.78	0.08	0.83
	N	9193	7901	7410	6982

Panel D: Aggregate mutual fund quarterly holding change after event quarter for *recent* High-DLI stocks

		Quarterly Holding Changes (Q+1 - Q) (%)	Quarterly Holding Changes (Q+2 – Q+1) (%)	Quarterly Holding Changes (Q+3 – Q+2) (%)	Quarterly Holding Changes (Q+4 – Q+3) (%)
	Mean	0.059	0.106	-0.116	0.169
Low	*t*-statistics	1.19	1.96	-2.22	3.00
	N	968	813	771	732
	Mean	-0.127	-0.284	0.035	-0.068
Medium	*t*-statistics	-1.79	-4.24	0.51	-0.97
	N	1091	999	931	885
	Mean	-0.584	-0.143	-0.097	0.134
High	*t*-statistics	-5.05	-1.37	-0.89	1.15
	N	404	391	376	353
	Mean	-0.129	-0.115	-0.045	0.056
All	*t*-statistics	-3.08	-2.81	-1.08	1.29
	N	2463	2203	2078	1970

Table X: Institutional trading at monthly frequency

Based on the institutional trading dataset provided by Plexus Group, for each stock in our sample during portfolio formation month, 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 at a monthly frequency. 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: Full sample (Q2 of 1991 to Q1 of 1993, Q1 of 1996 to Q1 of 1998)

Portfolio	Aggregate net buy/sell order (as % of total # of shares outstanding) by institutions (in %)	t-value	Aggregate shares bought/sold (as % of total # of shares outstanding) by institutions (in %)	t-value
Low DLI	0.02	2.91	0.01	1.91
2	0.01	0.28	-0.01	-0.47
3	0.03	2.01	0.02	2.42
4	0.06	3.31	0.03	3.03
5	0.06	3.98	0.04	3.39
6	0.04	1.11	0.05	1.80
7	0.03	0.55	0.04	1.24
8	-0.09	-1.22	-0.02	-1.41
9	-0.10	-2.45	-0.08	-2.41
High DLI	-0.18	-3.50	-0.14	-3.12
New High DLI	-0.14	-2.26	-0.11	-2.32

Panel B: Second sub-sample (Q1 of 1996 to Q1 of 1998)

Portfolio	Aggregate net buy/sell order (as % of total # of shares outstanding) by institutions (in %)	t-value	Aggregate shares bought/sold (as % of total # of shares outstanding) by institutions (in %)	t-value
Low DLI	0.03	2.34	0.02	1.95
2	-0.01	-0.14	-0.03	-0.40
3	0.04	1.71	0.04	2.20
4	0.07	3.87	0.06	3.21
5	0.09	4.79	0.08	4.27
6	0.12	1.70	0.09	1.68
7	0.13	1.67	0.10	1.66
8	-0.02	-0.51	-0.02	-0.68
9	-0.10	-1.72	-0.10	-1.76
High DLI	-0.15	-2.14	-0.15	-2.05
New High DLI	-0.13	-2.65	-0.12	-2.69

Table XI: Changes in liquidity-related characteristics during the liquidity shock

This table reports various stock characteristics during liquidity shock for 10 DLI-sorted deciles and also New High DLI stocks. New High DLI stocks are stocks which just enter into the highest-DLI decile during the current portfolio formation month.

Panel A reports the trading volume during three two-month periods: (1) the two months prior to the portfolio formation month ([-2.-1]); (2) the portfolio formation month and the first month after portfolio formation([0,1]); (3) the second and third month after portfolio formation ([2,3]). The trading volumes are adjusted for changes in the total number of shares outstanding. Finally, the trading volumes are normalized by the trading volume during the two months prior to the portfolio formation month ([-2.-1]). The sampling period is from 1970 to 1999.

Panel B reports the percentage bid-ask spread one month before portfolio formation, at portfolio formation and one month after portfolio formation. The percentage bid-ask spread is defined as (ask – bid) / mid. It is computed using intraday quote data from TAQ (after 1993) and ISSM (before 1993). The sampling period for NYSE stocks is from 1983 to 1999 and the sampling period for NASDAQ stocks is from 1987 to 1999.

Panel C reports two order imbalance measures during and one month after the portfolio formation month. Both measures are developed in Chordia, Roll and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004). OIBSH1 measures the buyer-initiated shares purchased less than the seller-initiated shares sold and OIBSH2 is OIBSH1 scaled by the total number of shares traded. The sampling period is from 1988 to 1998.

Panel D reports the average realized spreads (scaled by traded price) for each DLI decile and the portfolio of "new" high DLI stocks around portfolio formation month. The realized spread is computed using intraday quote data from1983 and 1999. The detailed estimation procedure is described in Huang and Stoll (1996). The time horizon used for the estimation is 30 minutes.

Panel E reports the liquidity betas during the portfolio formation month (0) and the first month after the portfolio formation month (1). It also reports the average liquidity betas during two three-month periods: the pre-formation - the three months prior to the portfolio formation month ([-3.-1]) and the post-formation – the second to fourth month after portfolio formation ([2,4]). As in Pastor and Stambaugh (2003), the liquidity beta during month n is defined as the slope coefficient (β^n) in the following regression:

$$r_{i,t}^n = \alpha_i^n + \beta_i^n L_t + \beta_{i,M}^n MKT_t + \beta_{i,S}^n SMB_t + \beta_{i,H}^n HML_t + \varepsilon_{i,t},$$

where r^0 denotes the excess return during portfolio formation month and MKT, SMB and HML are the Fama-French three factors. L is the innovation in the aggregate liquidity measure defined in Pastor and Stambaugh (2003). The changes in the liquidity betas over these periods are also reported, and the associated t-values are computed using Newey-West standard error estimators with three lags. The sampling period is from 1970 to 1999.

Panel A: Normalized trading volume

Portfolio	(1) Normalized Volume during Month [0,1]	t-value associated with (1)-1	(2) Normalized Volume during Month [2,3]	t-value associated with (2)-1
Low DLI	1.035	4.33	1.061	6.04
2	1.036	3.13	1.064	4.25
3	1.036	3.89	1.055	4.67
4	1.026	2.91	1.042	3.75
5	1.024	2.48	1.040	3.24
6	1.017	1.57	1.037	2.42
7	1.013	1.08	1.016	1.14
8	1.000	0.04	1.025	1.56
9	0.993	-0.57	1.025	1.31
High DLI	1.037	1.60	1.052	2.71
New High DLI	1.045	2.18	1.040	1.75

Panel B: Percentage trading cost

Portfolio	(1) Percentage spread 1 month prior to the formation (%)	(2) Percentage spread at formation (%)	(3) Percentage spread 1 month after formation (%)	t-value associated with (2)-(1)
Low DLI	1.36	1.35	1.36	-0.94
2	1.71	1.71	1.71	0.05
3	1.92	1.90	1.92	-1.51
4	2.30	2.27	2.30	-1.24
5	2.71	2.70	2.71	-0.55
6	3.18	3.17	3.18	-0.60
7	3.84	3.82	3.86	-0.53
8	4.95	4.94	4.98	-0.21
9	6.71	6.76	6.82	0.94
High DLI	10.68	11.01	11.04	3.63
New High DLI	7.22	8.31	8.23	10.53

Panel C: Order imbalance measures

Portfolio	(1) OIBSH1 during formation month	(2) OIBSH1 one month after formation	(2) - (1) Change in OIBSH1	t-value associated with (2) - (1)	(3) OIBSH2 during formation month (in %)	(4) OIBSH2 one month after formation (in %)	(4) - (3) Change in OIBSH2	t-value associated with (4) - (3)
Low DLI	10756.2	9885.6	-870.6	-3.87	0.91	0.51	-0.40	-5.42
2	11319.7	11466.3	146.6	0.17	-0.28	0.07	0.35	1.66
3	10128.5	10293.3	164.8	0.39	0.05	0.00	-0.05	-0.41
4	10314.2	10161.5	-152.7	-0.30	0.00	-0.12	-0.12	-0.92
5	9586.6	9539.7	-46.9	-0.09	-0.73	-0.77	-0.04	-0.25
6	8058.1	8747.4	689.3	1.20	-1.63	-1.32	0.31	1.87
7	6313.8	7416.9	1103.1	1.75	-2.56	-2.42	0.14	0.76
8	4312.7	5949.2	1636.5	2.52	-3.60	-3.40	0.20	0.88
9	1562.3	3698.0	2135.7	3.23	-5.76	-4.98	0.78	2.90
High DLI	-710.3	818.1	1528.4	2.03	-6.79	-6.05	0.74	2.35
New High DLI	-2456.6	2958.4	5415.0	2.87	-7.81	-4.26	3.55	5.67

Panel D: Huang and Stoll’s realized spread (scaled by traded price)

Portfolio	(1) Spread (in bps) one month before [month = -1]	(2) Spread (in bps) during formation [month = 0]	(3) Spread (in bps) one month after [month = 1]	(4) Spread (in bps) two month after [month = 2]	(2)-(1)	t-value for (2)-(1)	(4)-(3)	t-value for (4)-(3)
Low DLI	-0.5	-0.6	-0.6	-0.6	-0.1	-0.29	0.1	0.13
2	2.0	0.9	0.9	2.4	-1.1	-0.88	1.4	1.15
3	10.3	9.1	9.4	9.4	-1.2	-1.50	0.0	0.02
4	12.8	12.1	13.0	11.9	-0.7	-0.81	-1.0	-1.23
5	15.5	16.1	15.0	15.2	0.6	0.66	0.3	0.29
6	16.4	15.7	15.6	15.3	-0.7	-0.66	-0.3	-0.25
7	19.1	18.3	18.3	17.5	-0.8	-0.63	-0.8	-0.67
8	24.0	22.6	23.0	22.4	-1.4	-0.94	-0.6	-0.43
9	31.4	31.0	29.8	29.9	-0.5	-0.26	0.2	0.08
High DLI	58.1	59.8	58.9	57.5	1.7	0.75	-1.4	-0.61
New High DLI	31.7	49.9	53.8	43.8	18.3	3.76	-10.0	-2.01

Panel E: Pastor and Stambaugh's liquidity betas

Portfolio	(1) average liquidity beta during month=[-3,-1]	(2) liquidity beta during formation month = 0	(3) liquidity beta one month after month = 1	(4) average liquidity beta during month = [2,4]	(2)-(1)	t-value for (2)-(1)	(3)-(2)	t-value for (3)-(2)	(4)-(3)	t-value for (4)-(3)
Low DLI	0.002	0.006	0.026	0.016	0.004	0.39	0.021	3.07	-0.010	-2.19
2	-0.025	-0.022	-0.002	-0.006	0.002	0.17	0.020	1.39	-0.004	-0.34
3	-0.012	-0.014	-0.010	-0.008	-0.002	-0.14	0.004	0.42	0.001	0.14
4	-0.001	0.003	0.008	0.004	0.004	0.37	0.006	0.51	-0.004	-0.48
5	0.000	0.005	0.012	-0.008	0.005	0.47	0.007	0.53	-0.020	-2.18
6	0.000	-0.024	-0.009	-0.008	-0.024	-2.30	0.015	1.20	0.002	0.16
7	0.025	0.009	-0.002	-0.004	-0.016	-1.30	-0.011	-0.74	-0.003	-0.27
8	0.011	-0.001	-0.022	-0.016	-0.012	-0.84	-0.021	-1.45	0.006	0.58
9	0.002	0.004	-0.015	-0.006	0.002	0.11	-0.019	-1.15	0.009	0.72
High DLI	-0.080	-0.052	-0.110	-0.077	0.028	2.07	-0.058	-2.01	0.033	2.69
New High DLI	-0.078	0.036	-0.103	-0.069	0.114	2.39	-0.139	-2.11	0.034	0.61

Table XII: Cross-sectional regressions with stock characteristics

Each month from 1970/01 to 1999/12, we run a cross-sectional regression of the next month three-factor alphas on various current month stock characteristics. The alphas are estimated using rolling-window regressions. All variables are cross-sectionally demeaned so the intercept term is zero. In addition, 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 cross 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). Panel A reports the correlations among the characteristics (Full sample in lower-triangular and the Top DLI-quintile in the upper triangular). Panel B and C reports the regression results. The robust t value is reported below the coefficient estimate in italic. The regression slopes are presented in the unit of percentage return. For Panel B, the factor loadings are computed using monthly data in a five-year rolling window. For Panel C, the factor loadings are computed using daily data in a 6-month rolling window.

Panel A: Correlations

		Top DLI Quintile				
		Amihud	DLI	Size	B/M	Pret
Full Sample	Amihud		0.140	-0.190	0.103	0.016
	DLI	0.183		-0.232	0.353	-0.123
	Size	-0.143	-0.318		-0.208	0.034
	B/M	0.128	0.426	-0.362		-0.089
	Pastret	-0.003	-0.117	0.043	-0.106	

Panel B: Regression results (pre-formation factor loadings estimated using 5-year monthly data)

	Full sample							Top DLI-quntile						
	Pastret	Amihud	DLI	Size	B/M	Pastret* Amihud	R-square	Pastret	Amihud	DLI	Size	B/M	Pastret* Amihud	R-square
Model 1			0.217				0.80%			0.660				1.00%
			3.16							*5.73*				
Model 2		0.233					0.74%		0.592					1.21%
		3.56							*4.67*					
Model 3	-0.995						1.17%	-2.263						2.38%
	-9.70							*-13.35*						
Model 4	-1.004	0.200	0.037				2.47%	-2.244	0.541	0.265				4.44%
	-9.97	*3.22*	*0.61*					*-13.66*	*4.25*	*2.42*				
Model 5	-1.023	0.178	-0.084	-0.019	0.284		3.24%	-2.215	0.345	-0.066	-0.649	0.611		6.10%
	-10.19	*3.26*	*-1.60*	*-0.31*	*4.97*			*-13.44*	*2.97*	*-0.70*	*-4.36*	*5.02*		
Model 6	-0.877	0.043	-0.101	-0.033	0.288	-0.597	3.68%	-1.954	0.276	-0.086	-0.625	0.629	-0.639	7.02%
	-9.36	*0.54*	*-1.90*	*-0.56*	*5.21*	*-7.80*		*-11.93*	*1.40*	*-0.89*	*-4.34*	*5.31*	*-4.16*	

Panel C: Regression results (pre-formation factor loadings estimated using 6-month daily data)

	Full sample							Top DLI-quntile						
	Pastret	Amihud	DLI	Size	B/M	Pastret* Amihud	R-square	Pastret	Amihud	DLI	Size	B/M	Pastret* Amihud	R-square
Model 1			0.243				1.07%			0.622				0.99%
			3.22							*5.46*				
Model 2		0.274					0.92%		0.646					1.23%
		4.74							*6.04*					
Model 3	-0.801						0.98%	-2.080						2.10%
	-8.83							*-14.64*						
Model 4	-0.806	0.228	0.043				2.54%	-2.069	0.597	0.206				4.17%
	-9.24	*4.41*	*0.63*					*-14.63*	*5.57*	*1.90*				
Model 5	-0.829	0.188	-0.082	-0.052	0.314		4.24%	-2.040	0.382	-0.117	-0.664	0.618		6.07%
	-9.76	*4.09*	*-1.41*	*-0.47*	*3.96*			*-14.22*	*3.79*	*-1.26*	*-4.64*	*4.80*		
Model 6	-0.670	0.046	-0.100	-0.069	0.318	-0.656	4.71%	-1.754	0.336	-0.140	-0.643	0.635	-0.700	7.03%
	-8.65	*0.61*	*-1.71*	*-0.62*	*4.14*	*-8.51*		*-12.45*	*1.74*	*-1.48*	*-4.53*	*5.14*	*-4.68*	

Table XIII: Effect of bid-ask bounce

At the end of each month from 1970/12 to 1999/12, we sort all stocks into 10 deciles according to their DLIs (decile 1: Low DLI and decile 10: High DLI). We report the equally-weighted return during the first month after portfolio formation. We also report the measure for return bias (in bp) due to bid-ask bounce computed as $\left(\frac{P_A - P_B}{P_A + P_B}\right)^2$ where P_A and P_B are the bid and ask price of the stock. We first compute the return bias for the full sample (1970-1999) by assuming a constant bid-ask spread of \$0.25. We also compute the return bias using the actual quoted spread (quoted ask – quoted bid) from quote data in TAQ (after 1993) and ISSM (before 1993). The sampling period for NYSE stocks is from 1983 to 1999 and the sampling period for NASDAQ stocks is from 1987 to 1999. Finally, we compute the monthly return using daily returns from the second positive trading-volume-day.

DLI Decile #	Return one month after formation	Return bias due to bid-ask bounce Assuming a spread of \$0.25, 1970-1999 (in bp)	Return bias due to bid-ask bounce Using actual quoted spread, 1983-1999 (in bp)	First-month return excluding the return on the first trading day
1	0.0113	1.75	0.56	0.0112
2	0.0107	2.35	0.91	0.0106
3	0.0138	3.14	1.29	0.0138
4	0.0133	4.33	1.84	0.0132
5	0.0138	5.83	2.58	0.0137
6	0.0140	7.92	3.71	0.0139
7	0.0123	11.38	5.58	0.0123
8	0.0126	17.61	9.74	0.0124
9	0.0118	28.28	17.01	0.0118
10	0.0210	53.81	42.09	0.0202

Table XIV: Economic significance of the first-month high return on the High-DLI and New High-DLI stocks

We focus on the High-DLI stocks (stocks in the highest-DLI decile during the formation month) and New High-DLI stocks (stocks that enter the highest-DLI decile only during the formation month) and further sort them into quartiles according to their market capitalizations (in Panel A) or their trading prices (in Panel B). We then report various characteristics for each quartile. The percentage bid-ask spread and the return bias due to bid-ask bounce are both computed using the actual quoted spread (quoted ask – quoted bid) from quote data in TAQ (after 1993) and ISSM (before 1993). The sampling periods for these two characteristics are from 1983 to 1999 for NYSE stocks and from 1987 to 1999 for NASDAQ stocks. For other characteristics, the sampling periods are from 1971 to 1999.

Panel A: Size-sorted quartile

Quartile	# of stocks	Mktcap (million $)	Trading price	Return during formation month	Return one month after formation	Bid-ask spread (%)	Return bias due to bid-ask bounce (bp)
				High-DLI Stocks			
1	65	137.9	7.37	-0.0236	0.0037	5.18	11.08
2	65	13.6	3.51	-0.0257	0.0079	9.86	31.98
3	65	5.5	2.18	-0.0279	0.0152	14.27	63.65
4	65	2.0	1.27	-0.0585	0.0576	23.10	154.48
				New High DLI Stocks			
1	11	235.8	9.69	-0.0998	0.0199	3.69	5.50
2	12	21.8	4.93	-0.1170	0.0152	7.02	18.07
3	12	8.4	3.19	-0.1424	0.0234	10.70	39.93
4	11	3.0	1.79	-0.1801	0.0619	18.89	128.84

Panel B: Price-sorted quartile

Quartile	# of stocks	Mktcap (million $)	Trading price	Return during formation month	Return one month after formation	Bid-ask spread (%)	Return bias due to bid-ask bounce (bp)
				High-DLI Stocks			
1	65	123.3	8.56	-0.0177	0.0058	4.82	10.18
2	65	21.4	3.26	-0.0240	0.0074	9.21	29.78
3	66	9.6	1.77	-0.0324	0.0161	14.58	70.41
4	65	4.9	0.77	-0.0618	0.0553	23.80	147.50
				New High DLI Stocks			
1	11	209.3	11.14	-0.0852	0.0154	3.61	6.32
2	12	39.5	4.73	-0.1169	0.0176	6.74	17.49
3	12	14.3	2.63	-0.1449	0.0289	10.79	43.43
4	11	6.2	1.19	-0.1921	0.0582	19.71	127.92