JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 45, No. 1, Feb. 2010, pp. 27–48

doi:10.1017/S0022109010000013

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

Zhi Da and Pengjie Gao*

Abstract

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

I. Introduction

The pricing of financial distress or default risk is one of the fundamental questions in financial economics. In a recent study, Vassalou and Xing (2004) measure default risk using a default likelihood indicator (DLI) computed according to the Black-Scholes (1973) and Merton (1974) option pricing framework and show that stocks more likely to default earn higher returns than otherwise similar stocks. Their finding represents a puzzle for the literature on financial distress or

*Da, zda@nd.edu, and Gao, pgao@nd.edu, Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556. We are grateful to Nicholas Barberis, Robert Battalio, Hendrik Bessembinder (the editor), Nicolas Bollen, Nai-fu Chen, Tarun Chordia (AFA discussant), Shane Corwin, Kent Daniel, Darrell Duffie, Andrea Eisfeldt, Larry Glosten, Joel Hasbrouck, Steve Hillegeist, Jennifer Huang, Gergana Jostova (NBER discussant), Ivalina Kalcheva, Leonid Kogan, Bob Korajczyk, Anthony Lynch, Ron Masulis, Mitchell Peterson, Christopher Polk, Todd Pulvino, Ernst Schaumburg, Michael Schill (FMA discussant), Paul Schultz, S. "Vish" Viswanathan, and Robert Whitelaw; and seminar participants at Arizona State University, Columbia University, Lehman Brothers, Northwestern University, New York University, University of California-Irvine, University of Texas at Austin, University of Notre Dame, University of Pennsylvania, Vanderbilt University, the FMA 2005 annual meeting, the NBER market microstructure 2006 conference, and the AFA 2007 annual meeting for their helpful comments. We thank Ravi Jagannathan for guidance and support. We are grateful to John Griffin (the referee), whose comments substantially improved both the content and exposition of the paper. We also thank Tarun Chordia, Kenneth French, Donald Keim, Ananth Madhavan, Luboš Pástor, Maria Vassalou, Wayne Wagner, and Sunil Wahal for making data available. Part of the results in this paper have previously appeared in an unpublished working paper entitled "Default Risk and Equity Return: Macro Effect or Micro Noise." We are responsible for all remaining errors.

default risk, as most recent research documents the opposite relation (see Dichev (1998), Griffin and Lemmon (2002), Garlappi, Shu, and Yan (2008), Campbell, Hilscher, and Szilagyi (2008), and George and Hwang (2010)). We resolve this puzzle by relating Vassalou and Xing's (2004) finding to the short-term return reversal first documented by Jegadeesh (1990) and Lehman (1990). In addition, we analyze a concrete channel through which a liquidity shock might occur on a stock that in turn causes the return reversal.

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

To reconcile these two puzzling findings by Vassalou and Xing (2004) with the literature, our investigation first reveals that stocks in the highest DLI decile earn abnormal returns only in the first month after portfolio formation. The returns on these stocks immediately decline by more than one-quarter, from 2.10% in the first month to 1.52% in the second month, and stabilize afterward. If we skip a month and use the second-month returns in various asset pricing tests, we find that the returns of high default risk stocks can be fully explained by the Fama-French (1993) three-factor model, and the additional default risk factor is no longer needed. We also verify that characteristics such as size, BM ratio, default likelihood, and loadings on risk factors barely change from the first to the second month after portfolio formation. Second, we show that abnormal returns on the highest DLI decile are confined to a small subset of stocks with similar DLIs that recently experienced large negative returns and sharp increases in their DLI measure (the high-DLI losers). Thus, the abnormal return on high default risk stocks documented in Vassalou and Xing (2004) is temporary and clearly does not represent compensation for bearing systematic default risk.

Empirically, high default risk stocks are recent losers on average during the portfolio formation month, so their abnormal returns in the subsequent month constitute a short-term return reversal, a robust empirical regularity first uncovered by Jegadeesh (1990) and Lehman (1990). In a cross-sectional regression framework, we confirm that the past 1-month returns drive out DLI in predicting the next-month stock returns.

What could be the possible causes of such short-term return reversal on default risk stocks? The evidence suggests that it is likely the result of price pressure caused by a liquidity shock around portfolio formation. The link between short-run reversal and liquidity shock has been discussed by Campbell, Grossman, and Wang (1993), Conrad, Hameed, and Niden (1994), and more recently by

Avramov, Chordia, and Goyal (2006). They find greater return reversals in high-turnover, illiquid stocks and attribute such return reversals to non-information-based demands for immediacy. The changes in various liquidity characteristics of high-DLI stocks largely support such an argument. Unlike the existing literature, however, we can identify at least one plausible economic reason behind such demands for immediacy on high-DLI stocks: a financial distress-induced clientele change.

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

Stocks associated with high default risk are likely to be penny stocks, and their average bid-ask spread as a percentage of trading price is relatively high. The bid-ask bounce could cause a sizable upward bias in average return computation, as noted by Blume and Stambaugh (1983) and recently by Asparouhova, Bessembinder, and Kalcheva (2010). Computation of the bid-ask bounce bias and recalculation of the monthly stock returns excluding the first trading day after portfolio formation both demonstrate that the abnormal returns on high-DLI stocks are driven by more than just bid-ask bounce bias.

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

Our findings contribute to a growing literature on the relation between default risk and stock returns by reconciling Vassalou and Xing (2004) with other findings. Campbell, Hilscher, et al. (2008) examine annual returns where the short-term liquidity-induced return reversal plays a smaller role, while Garlappi et al. (2008) focus on second-month returns. As financially distressed stocks are usually small stocks and prone to liquidity shock, our findings highlight the importance of accounting for liquidity shocks in the empirical examination of default or financial distress risk. This is especially true when the default risk measure is computed directly using the market price of a stock.

Our findings also add to the literature that analyzes the impact of liquidity shocks on asset prices. Related work includes Grossman and Miller (1988) and Coval and Stafford (2007). These authors argue that liquidity shocks have a large and persistent impact on asset prices, which we confirmed. The empirical challenge is to identify the economic mechanisms underlying such a liquidity shock. That is, why do agents decide to trade a large amount of particular assets at the same time? We contribute in this regard by providing one plausible explanation: a sharp increase in default risk. When a stock experiences a sharp increase in default risk, financial institutions with binding investment restrictions have to sell the stock immediately, creating a liquidity shock.

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

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

II. Brief Review of Default Risk Measures

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

Most recently, researchers start to use various direct measures of default or financial distress risk. For instance, Dichev (1998), Griffin and Lemmon (2002), and George and Hwang (2010) use accounting bankruptcy measures for distress risk such as Altman's (1968) Z-score and Ohlson's (1980) O-score; Garlappi et al. (2008) use Moody's KMV's expected default frequencies$^{\text{TM}}$; Campbell, Hilscher, et al. (2008) consider their own version of default predictor. In all of these studies, default or financial distress risk is shown to be negatively associated with stock returns, especially when the default risk is higher.

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

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

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

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

To compute DLI, Vassalou and Xing (2004) use three economically sensible inputs: V_A/X, μ, and σ_A. Empirically, μ, computed as the mean of changes in $\ln V_A$, is closely related to stock returns (RET); V_A/X is closely related to financial leverage ($\text{LEV} = D/E$), as $V_A/X \simeq 1 + 1/\text{LEV}$; and 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 the firm asset value, so σ_A is also closely related to the stock return volatility. DLI can be thought of as an all-in-one measure, defined as a nonlinear transformation of leverage with two additional variables (i.e., $\text{DLI}=f(\text{LEV}, \text{RET}, \sigma_A)$). In an unreported variance decomposition exercise, we find that past stock returns are an important determinant of DLI, especially among stocks in the top DLI decile.[1] This should not surprise us, as DLI is estimated directly using current stock price. In the next section, we examine in detail the role of past returns in driving Vassalou and Xing's (2004) findings.

III. Default Risk or Short-Term Return Reversal?

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

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

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

TABLE 1

Characteristics of 10 DLI-Sorted Portfolios

At the end of each month during the period from 1971 to 1999, we sort all stocks into 10 deciles according to DLI (decile 1 (low DLI) and decile 10 (high DLI)). We report the equal-weighted characteristics of these portfolios. The AMIHUD illiquidity measures are multiplied by 1,000. The average analyst coverage is estimated during the period from 1984 to 1990.

Port ID	DLI (%)	First-Month Return	MKT_CAP (in millions)	BM	Past 1-Year Return (%)	Past 1-Month Return (%)	Price	AMIHUD	IDIO_RISK	% Covered by Analysts	No. of Analysts
1	0.00	0.0113	2,164.92	0.62	12.39	2.48	52.12	0.47	86.30%	73.50%	5.39
2	0.00	0.0107	1,303.78	0.73	14.49	2.31	29.37	0.92	86.50%	76.70%	4.98
3	0.00	0.0138	926.84	0.75	14.28	2.70	24.48	0.87	88.20%	67.40%	4.55
4	0.01	0.0133	644.64	0.78	14.41	2.68	20.06	1.29	89.00%	62.60%	4.20
5	0.04	0.0138	452.80	0.83	13.80	2.40	17.02	1.56	89.90%	57.00%	3.80
6	0.17	0.0140	339.21	0.89	12.21	2.08	14.52	2.51	90.80%	51.70%	3.42
7	0.61	0.0123	225.86	0.99	8.37	1.67	11.51	3.52	91.90%	44.90%	3.11
8	2.15	0.0126	141.27	1.12	0.75	0.86	8.77	6.24	93.30%	36.60%	2.87
9	7.85	0.0118	80.72	1.32	−15.27	-0.22	6.12	11.54	94.80%	29.10%	2.60
10	36.45	0.0210	39.60	1.92	-51.96	-3.39	3.58	31.75	96.60%	20.30%	2.50

Table 1 also documents other characteristics of the 10 DLI-sorted portfolios. As in Vassalou and Xing (2004), the highest DLI stocks are associated with the smallest size and highest BM ratios. The highest DLI stocks are clearly past losers. They lost 51.96% in the last year and 3.39% in the last month. Not surprisingly, high-DLI stocks also trade at low prices. In fact, the average price declines monotonically with DLI. The highest DLI stocks trade at a mean of $3.58. The low trading price makes the percentage transaction cost much higher for financially distressed stocks, thus making them more illiquid at the same time.

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

$$\text{AMIHUD}_t \quad = \quad \frac{1}{T}\sum_{d=1}^{T}\frac{|R_{i,t-d}|}{\text{VOL}_{i,t-d}}. \tag{2}$$

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

In the third from the last column, Table 1 reports the average idiosyncratic risk measures for stocks by decile. For each month and each stock, we regress the daily stock excess returns on the Fama-French (1993) three factors over the past 6 months, and take the $1 - R^2$ (where R^2 is the adjusted-R^2) as a measure of firm-level idiosyncratic risk. The idiosyncratic risk measure increases monotonically with DLI. For stocks with the highest DLI, nearly 97% of the total risk is idiosyncratic. In the lowest DLI decile, 74% of stocks receive analyst coverage; 5.4

analysts on average follow each stock, if the stock receives analyst coverage at all. Only 20% of stocks in the highest DLI decile receive analyst coverage, and in this case, there are only 2.5 analysts per stock if the stock receives analyst coverage at all.

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

A. First Month versus Second Month

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

The returns of the high-DLI portfolio (including stocks in the highest DLI decile) immediately drop by more than one-quarter, from 2.10% in the first month to 1.52% in the second month after portfolio formation. This drop of 58 bp is highly significant (with a t-value above 10). A low-DLI stock portfolio, which includes stocks in DLI deciles 1–5, on the other hand, earns slightly more during the second month than the first month (1.37% compared to 1.28%). The return difference between the high-DLI portfolio and the low-DLI portfolio is only positive and significant during the first month but not in the second. Once we skip the first month and look at long-run portfolio returns in months 2–6 and months 2–12 after portfolio formation, the stocks in the highest DLI decile now earn lower returns than those in the low-DLI portfolios, consistent with findings in the recent literature. The high-low return spreads after the first month are both negative and significant.

Panel B of Table 2 reports the Fama-French (1993) three-factor risk-adjusted returns and factor loadings. For the high-DLI portfolio, a simple time-series regression of its first-month return on the Fama-French three factors yields a significant positive alpha of 64 bp. This finding is consistent with the asset pricing test results in Vassalou and Xing (2004), and it seems to indicate that the return on high default risk stocks is too high to be explained by the standard Fama-French three factors.

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

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

TABLE 2

First-Month versus Second-Month Returns after Portfolio Formation

Table 2 compares the first- and second-month returns after portfolio formation for DLI-sorted portfolios. Low-DLI stocks are stocks in DLI deciles 1–5, and high-DLI stocks are stocks in the highest DLI decile. Panel A reports average returns. Panel B reports three-factor (Fama and French (1993)) risk-adjusted returns and the factor loadings. Panel C reports the characteristics-adjusted returns and average characteristics. The characteristics-adjusted return is computed as the excess return over a benchmark portfolio constructed by matching along size, book-to-market (BM), and momentum characteristics. Panel D reports the results of cross-sectional generalized method of moments (GMM) tests. The tests are performed on 2 sets of portfolio returns: i) the equal-weighted monthly returns on 10 DLI-sorted portfolios; ii) the equal-weighted monthly returns on 27 portfolios sorted on size, BM equity, and DLI. MKT is 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 stocks and short on large stocks; the GMM estimations use an optimal weighting matrix; and *J*-Stat. denotes the test statistic on the model overidentification restriction. The sampling period is from January 1971 to December 1999.

Panel A. Average Portfolio Returns

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

Panel B. Factor-Adjusted Returns and Factor Loadings

	Three-Factor-Adjusted Alpha (%)				Factor Loadings					
	Month = 1		Month = 2		Month = 1			Month = 2		
Portfolio	Mean	*t*-Value	Mean	*t*-Value	MKT	SMB	HML	MKT	SMB	HML
Low-DLI	0.03	0.61	0.14	1.02	0.90	0.75	0.09	0.89	0.72	0.09
High-DLI	0.64	2.33	0.03	0.13	1.13	1.85	0.75	1.09	1.79	0.75
High − Low	0.62	2.27	−0.11	−0.41	0.23	1.10	0.66	0.20	1.07	0.65

Panel C. Characteristics-Adjusted Returns and Portfolio Characteristics

	Characteristics-Adjusted Return (%)				Characteristics at Formation			Characteristics 1 Month after Formation		
	Month = 1		Month = 2							
Portfolio	Mean	*t*-Value	Mean	*t*-Value	DLI (%)	MKT_CAP (in millions)	BM	DLI (%)	MKT_CAP (in millions)	BM
Low-DLI	−0.02	−0.59	0.04	0.92	0.1	1,283.6	0.72	0.1	1,301.9	0.73
High-DLI	0.69	4.08	0.04	0.24	36.4	41.0	1.92	34.9	42.1	1.89
High − Low	0.72	3.64	0.00	0.01	36.3	−1,242.5	1.19	34.8	−1,259.8	1.16

Panel D. Cross-Sectional GMM Test Results

	10 DLI-Sorted Portfolios											
	First-Month Returns						Second-Month Returns					
Variable	Constant	MKT	SMB	HML	DSV	*J*-Stat.	Constant	MKT	SMB	HML	DSV	*J*-Stat.
Coeff.	0.85	13.43	−17.02	24.75		49.77	0.88	8.77	−11.47	19.15		14.76
t-value	10.31	1.72	−2.38	2.38		0.00	14.69	1.65	−2.18	2.34		0.02
Coeff.	0.81	12.00	21.17	38.43	−132.17	8.38	0.84	12.44	−6.50	25.18	−33.12	7.63
t-value	6.79	1.28	1.56	2.90	−3.08	0.14	10.26	1.77	−0.86	2.36	−1.11	0.18

	27 Size-/BM-/DLI-Sorted Portfolios											
	First-Month Returns						Second-Month Returns					
Variable	Constant	MKT	SMB	HML	DSV	*J*-Stat.	Constant	MKT	SMB	HML	DSV	*J*-Stat.
Coeff.	1.00	0.82	0.53	−5.13		163.05	0.98	1.77	−1.32	−3.42		113.12
t-value	44.31	0.41	0.23	−1.86		0.00	46.22	0.85	−0.58	−1.23		0.00
Coeff.	0.93	4.88	7.85	−5.21	−39.44	133.69	0.95	4.55	3.29	−2.02	−25.98	111.37
t-value	28.95	1.76	1.89	−1.68	−2.15	0.00	27.99	1.35	0.74	−0.62	−1.17	0.00

These excess returns are then equal weighted to form the portfolio characteristics-adjusted return.

Once again, for the high-DLI stock portfolio, the first-month characteristics-adjusted return is positive and significant (0.69% with a t-value of 4.08), but the second-month characteristics-adjusted return is much lower and insignificant (0.04% with a t-value of 0.24). The drop of 65 bp resembles what we find for the three-factor model. The characteristics-adjusted returns on the low-DLI portfolio, however, are insignificant whether we use the first- or the second-month return. Even with characteristics adjustment, the high-low return spread is significant only during the first month.

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

$$\mathrm{E}[mR] = 1,$$

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

Consistent with the results in Vassalou and Xing (2004), for the 10 DLI-sorted portfolios and the first-month returns, an aggregate default risk factor (DSV) computed as the changes in the average DLI across all stocks, is significant even with the presence of the Fama-French (1993) three factors. The significance of DSV disappears in second-month returns. Similar results are obtained when we repeat the GMM tests on the 27 portfolios formed by independent triple sorts on DLI, size, and BM ratios as in Vassalou and Xing (2004); DSV becomes insignificant once we use second-month returns even though the risk characteristics of the stock do not change significantly after 1 month for the 27 portfolios.

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

B. DLI versus Past Returns

High-DLI stocks are recent losers. Which factor then explains their abnormal first-month return: DLI or the past 1-month return? To address this question, we first use a double sort. Every month, we first sort the stocks in the top DLI decile into quintiles on DLIs. Within each quintile, we further sort stocks into 5 portfolios on the past 1-month returns. This sequential double sort results in 25 portfolios. The average DLIs and returns are provided in Table 3.

TABLE 3

DLI/Past One-Month Return Sort within High-DLI Decile

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

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

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

Sorting stocks into portfolios according to one characteristic will inevitably induce dispersion along the dimensions of other characteristics. To control for these characteristics simultaneously, we therefore use a cross-sectional regression approach at the individual stock level. If the first-month high returns on high-DLI stocks are in fact driven by high default risk, and DLI captures default risk better than other stock characteristics, we would expect DLI to be significant in the cross-sectional regression even in the presence of other stock characteristics. Conversely, if the first-month high return is a result of the short-term return reversal, we would expect the past 1-month return to always be strongly significant. Finally, as financially distressed stocks are typically illiquid, we would also expect the liquidity measure AMIHUD, among other stock characteristics, to be significant in the regression.

Table 4 presents the results of the cross-sectional regressions. For each month in the 1971–1999 period, we run a cross-sectional regression of the next-month stock return on various stock characteristics for the current month. All variables are cross-sectionally demeaned, so the intercept term of the regression is 0. Stock characteristics are standardized so that the regression slope coefficient of a variable can be interpreted as the impact on the return of a 1-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 (1987) autocorrelation-adjusted standard error with 12 lags. We consider the variables, PAST_RET (stock return during the month prior to portfolio formation), AMIHUD, DLI, SIZE (log of market capitalization), and BM ratio. We exclude stocks with missing characteristics and negative BM.

TABLE 4

Cross-Sectional Regressions with Stock Characteristics (1971–1999)

We run monthly cross-sectional regressions of the next-month stock returns on various current month stock characteristics. All variables are cross-sectionally demeaned so the intercept term is 0. The stock characteristics are also standardized so the regression slope coefficient can be interpreted as the impact on the return of a 1-standard-deviation change in the variable. The slope coefficients are then averaged across time and reported. The robust t-value is computed using the Newey-West (1987) 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; BM is the book-to-market ratio; and PAST_RET is the return 1 month prior to the portfolio formation. We exclude stocks with missing characteristics and negative BM. The regressions are estimated for both the full sample (1,589 stocks per month on average) and the top DLI quintile (272 stocks per month on average). The robust t-value is reported below the coefficient estimate in parentheses.

First-Month Return (%)	PAST_RET	AMIHUD	DLI	SIZE	BM	PAST_RET × AMIHUD	R^2
Panel A. Full Sample							
Model 1			0.25				1.07%
			(3.22)				
Model 2		0.28					0.92%
		(4.75)					
Model 3	−0.80						0.98%
	(−8.78)						
Model 4	−0.80	0.23	0.05				2.55%
	(−9.18)	(4.41)	(0.65)				
Model 5	−0.83	0.19	−0.08	−0.05	0.31		4.26%
	(−9.71)	(4.11)	(−1.37)	(−0.47)	(3.93)		
Model 6	−0.67	0.05	−0.10	−0.07	0.32	0.65	4.73%
	(−8.60)	(0.65)	(−1.67)	(−0.62)	(4.11)	(−8.28)	
Panel B. High-DLI Quintile							
Model 1			0.62				1.00%
			(5.48)				
Model 2		0.65					1.24%
		(6.08)					
Model 3	−2.08						2.10%
	(−14.64)						
Model 4	−2.07	0.60	0.21				4.16%
	(−14.62)	(5.59)	(1.93)				
Model 5	−2.04	0.38	−0.11	−0.66	0.62		6.07%
	(−14.22)	(3.78)	(−1.22)	(−4.62)	(4.81)		
Model 6	−1.75	0.35	−0.14	−0.64	0.64	−0.67	7.03%
	(−12.46)	(1.79)	(−1.43)	(−4.51)	(5.16)	(−4.17)	

Panel A of Table 4 reports the regression results for the full sample, with about 1,600 stocks in each cross section. In the first three regressions (Models 1–3), the only regressor is either DLI, AMIHUD, or PAST_RET. Either DLI, AMIHUD, or PAST_RET individually is significantly associated with the next-month stock return. PAST_RET is strongly significant (t-value of -9.71), and AMIHUD is slightly more significant than DLI (t-value of 4.75 for AMIHUD vs. 3.22 for DLI). DLI, however, becomes insignificant in the presence of PAST_RET and AMIHUD (Model 4). Model 5 also controls for SIZE and BM. Now DLI is not significant and assumes the wrong sign, but PAST_RET and AMIHUD are still significant.

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

To summarize, we find that the abnormal first-month return on high-DLI stocks is the manifestation of the short-term return reversal, a well-known stock return pattern (Jegadeesh (1990), Lehman (1990)). This finding helps to reconcile Vassalou and Xing's (2004) findings with the recent literature. Recent authors have adopted empirical procedures that mitigate the effect of such a return reversal. For instance, motivated by our findings, Garlappi et al. (2008) in their empirical exercise skip the first month and focus on second-month returns. Campbell, Hilscher, et al. (2008) specifically examine annual returns after portfolio formation, which minimizes the impact of the first-month reversal. Finally, in several of their empirical exercises, George and Hwang (2010) exclude the month of January when reversals are the greatest.

IV. Explaining the Short-Term Return Reversal

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

A. Price Pressure from Institutional Selling

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

1. Liquidity Shocks

Since high-DLI stocks on average are more illiquid, their greater return reversals could be consistent with a price-pressure-based explanation. We provide some supporting evidence in Table 5, where we examine 4 stock portfolios: i) the low-DLI stock portfolio, which includes stocks in DLI deciles 1–5; ii) the high-DLI stock portfolio, which includes stocks in the highest DLI decile; iii) the high-DLI loser portfolio, which includes 20% of high-DLI stocks with relatively low

TABLE 5

Institutional Trading and Changes in Liquidity Characteristics

Table 5 reports results on institutional trading and changes in liquidity characteristics on low-DLI stock portfolios (including stocks in DLI deciles 1–5), high-DLI stock portfolios (including stocks in the highest DLI decile), high-DLI losers (including 20% of high-DLI stocks with relatively low past 1-month returns after controlling for DLI) and other high-DLI stocks (including high-DLI stocks that are not high-DLI losers). Panel A reports the average liquidity characteristics during the second month prior to formation (month = −2) and the month prior to formation (month = −1). TURNOVER is defined as monthly trading volume divided by total number of shares outstanding (SHR_OUT); AMIHUD is an illiquidity measure; OIMB is defined as the number of buyer-initiated shares purchased less the number of seller-initiated shares sold, scaled by the total number of shares outstanding; PQ_SPREAD measures the average percentage quoted spread, defined as (ASK − BID)/MID; PE_SPREAD measures the average percentage effective spread, defined as $2|P - \text{MID}|/\text{MID}$; and PR_SPREAD measures the percentage realized spread. Its detailed estimation procedure is described in Huang and Stoll (1996). The time horizon used for the estimation is 30 minutes. The sampling period is 1971–1999. All the spread-based measures are computed using intraday quote data from TAQ (after 1993) and ISSM (before 1993). The sampling period for NYSE/AMEX stocks is from 1983 through 1999, and the sampling period for NASDAQ stocks is from 1987 through 1999. Panel B reports the aggregate mutual fund (MF) holdings before and after the portfolio formation and the implied holding changes. Panel C reports the aggregate institutional holding changes around the portfolio formation across various types of institutions. Panel D reports institutional trading activities using a data set provided by the Plexus Group. For each stock during the month prior to formation, we first compute the aggregate net buy/sell orders (as the percentage of total number of shares outstanding) submitted by institutions and actual aggregate shares bought/sold (again as the percentage of total number of shares outstanding) by institutions. We then average these 2 institutional trading measures first across all stocks at portfolio level and then across time. A negative number indicates net selling.

Panel A. Average Liquidity Characteristics

	Month				Month				Month			
	−2	−1	Change	t-Value	−2	−1	Change	t-Value	−2	−1	Change	t-Value
Portfolio	TURNOVER, Volume/SHR_OUT				AMIHUD				OIMB, (#BUY − #SELL)/SHR_OUT			
Low-DLI	0.0566	0.0564	0.0017	0.65	0.0012	0.0013	0.0001	1.35	0.0066	0.0070	0.0005	0.63
High-DLI	0.0498	0.0500	0.0002	0.20	0.0297	0.0318	0.0021	3.01	−0.0100	−0.0098	0.0000	−0.11
High-DLI loser	0.0612	0.0669	0.0057	2.81	0.0296	0.0411	0.0115	6.51	0.0009	−0.0357	−0.0367	−6.64
Other high-DLI	0.0471	0.0459	−0.0012	−1.72	0.0296	0.0295	−0.0002	−0.25	−0.0115	−0.0061	0.0052	1.94
Portfolio	PQ_SPREAD				PE_SPREAD				PR_SPREAD			
Low-DLI	0.0203	0.0203	0.0000	−1.76	0.0144	0.0144	0.0000	0.13	0.0002	0.0005	0.0003	−1.10
High-DLI	0.0987	0.1008	0.0024	4.06	0.0732	0.0748	0.0019	2.79	0.0092	0.0099	0.0007	0.65
High-DLI loser	0.0982	0.1144	0.0166	15.95	0.0732	0.0844	0.0115	11.38	0.0112	0.0183	0.0073	5.36
Other high-DLI	0.0989	0.0975	−0.0011	−0.64	0.0732	0.0725	−0.0004	−0.65	0.0086	0.0078	−0.0008	−1.08

Panel B. Aggregate Quarterly Mutual Fund Holdings and Holding Changes

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

(continued on next page)

TABLE 5 (continued)

Institutional Trading and Changes in Liquidity Characteristics

Panel C. Institutional Holding Changes by Types of Institutions

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

Panel D. Monthly Institutional Trading

	Full Sample (1991Q2–1993Q1, 1996Q1–1998Q1)				Earlier Periods Excluded (1996Q1–1998Q1)			
Portfolio	Net Buy/ Sell Order as % of SHR_OUT	*t*-Value	Net Shares Bought/Sold as % of SHR_OUT	*t*-Value	Net Buy/ Sell Order as % of SHR_OUT	*t*-Value	Net Shares Bought/Sold as % of SHR_OUT	*t*-Value
Low-DLI	0.04%	4.42	0.02%	3.82	0.05%	4.28	0.04%	4.31
High-DLI	−0.18%	−3.50	−0.14%	−3.12	−0.15%	−2.14	−0.15%	−2.05
High-DLI loser (1)	−0.41%	−2.37	−0.33%	−1.96	−0.26%	−3.02	−0.25%	−2.88
Other high-DLI (2)	−0.14%	−2.70	−0.11%	−2.34	−0.12%	−1.51	−0.12%	−1.46
(1) − (2)	−0.27%	−2.28	−0.22%	−1.96	−0.14%	−2.40	−0.13%	−2.33

past 1-month returns after controlling for DLI; and iv) another high-DLI stock portfolio, which includes the remaining 80% of high-DLI stocks that are not in the high-DLI loser portfolio.

For each portfolio, we tabulate in Panel A of Table 5 the average liquidity-related portfolio characteristics 2 months and 1 month prior to portfolio formation, the difference, and the *t*-value associated with the difference. These liquidity characteristics include: TURNOVER (monthly trading volume divided by total number of shares outstanding); AMIHUD; OIMB (an order imbalance measure, defined as the number of buyer-initiated shares purchased less the number of seller-initiated shares sold, scaled by the total number of shares outstanding); PQ_SPREAD (the percentage quoted spread, defined as the ratio between the quoted bid-ask spread and the midpoint of the quoted bid and ask); PE_SPREAD (the percentage effective spread, defined as $2|P - \text{MID}|/\text{MID}$); and PR_SPREAD (the percentage realized spread). PE_SPREAD allows for the possibility that a trade could take place within the bid-ask spread, which explains why it is smaller in size. PR_SPREAD measures the reward to market makers for providing liquidity. A detailed estimation procedure is described in Huang and Stoll (1996). The time horizon used for the estimation is 30 minutes. The OIMB measure and the spread-based measures are computed using intraday quote data from the Trade and Quote (TAQ) database (after 1993) and from the Institute for the Study of Security Markets (ISSM) (before 1993). The sampling period for NYSE/AMEX stocks is 1983–1999, and the sampling period for NASDAQ stocks is 1987–1999.

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

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

2. Clientele Changes

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

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

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

The mutual fund holding data come from the CDA Investment Technologies (CDA)/Spectrum mutual fund holding database, which collects holding information from N30-D filings to the SEC. Since small holdings are exempt from reporting by SEC regulations, mutual fund holdings may be truncated at the lower end.[2] It is thus likely that the number of mutual fund shareholders is understated according to CDA/Spectrum, but the resulting impact should be relatively small. To assess the bias, we further sort the stocks into three groups based on the breadth of ownership and obtain similar results across the three groups. We report in Panel B of Table 5 statistics from the full sample (1980–1999) and two subsamples (1980–1989 and 1990–1999) to ensure that the results are not driven by the later period, when there is a dramatic increase in the number of mutual funds.

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

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

In Panel C of Table 5, we document a similar clientele change using the CDA/Spectrum Institutional 13F Stock Holdings and Transactions database, which reports quarterly transactions and holdings by institutional investors. As in the case of mutual funds, we infer institutional trading activities by looking at aggregate quarterly institutional holding changes when stocks become financially distressed. We then report the average holding changes from 1980 through 1999 across 5 types of institutions including banks, insurance companies, investment companies, investment advisors, and other institutions. Most institutions (except those in the others category) significantly reduce their holdings of high-DLI stocks but not the low-DLI stocks. In addition, the institutional selling pressure is much heavier on high-DLI losers than on other high-DLI stocks. The total quarterly holding change across all institutions on the high-DLI loser portfolio is -3.58%, much higher than the change on the other high-DLI stock portfolio (-2.20%). The difference is highly significant for most institutions, except insurance companies as a group. In conclusion, although some institutions are buying high-DLI stocks, all

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

[3]In most cases, $H_{i,j,t-}$ and $H_{i,j,t+}$ are one quarter apart. For a small portion of mutual funds that report holdings on a semiannual basis, they are 6 months apart.

the institutions as a group are selling high-DLI stocks and high-DLI losers in particular. This clientele change is consistent with recent findings on individual and institutional trading behavior. For instance, Kaniel et al. (2008) show that individuals tend to buy NYSE stocks (inferring institutional selling) following declines in the previous month.

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

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

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

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

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

The selling of financially distressed stocks by institutional investors such as mutual funds is unlikely to be absorbed by ready outside buyers, as it takes time and human capital for an investor to identify a profitable opportunity and then act on it (see Berndt, Douglas, Duffie, Ferguson, and Schranz (2005)). We believe such "capital immobility" to be especially relevant for the trading of financially distressed stocks. The results of distressed securities investing depend on an investor's efficiency in uncovering and analyzing all the variables specific to the distressed company. The investor "will not only know everything about the company and its financials but will have studied the creditors involved in the reorganization as well: their numbers, their willingness to compromise, and the complexity of their claims help indicate how long the reorganization will last, what the asset distributions will be, and whether the expected returns are worth the wait" (see Friedland (2005), p. 1). Gathering and analyzing such firm-specific information is a daunting task and very time consuming. The absence of Wall Street research coverage on distressed firms makes the job even harder. When there is heavy selling pressure and a lack of immediate ready buyers, the liquidity shock can be persistent, and the price concession can last for a few days or even up to a month for financially distressed stocks.

B. Bid-Ask Bounce Bias

By construction, firms that are facing financial distress or considerable default risk are typically associated with small market capitalization and low trading prices. The average market value and trading price of high-DLI stocks are $39.6 million and $3.58, respectively. One particular problem associated with stocks traded at low prices is that the random bid-ask bounce could lead to a nonnegligible upward bias in average return computation, as discussed in Blume and Stambaugh (1983) and more recently in Asparouhova et al. (2010). In fact, bid-ask bounce is often one of the reasons researchers skip a week or a month between portfolio formation and the portfolio holding period in return momentum studies. Mech (1993) discusses several ways of controlling for bid-ask bounce in portfolio return calculation. A natural question is whether the first-month high returns on the highest DLI stock portfolio are entirely driven by bias due to such a bid-ask bounce. To address this question, we first estimate the impact of the bid-ask bounce on returns. Blume and Stambaugh (1983) show that the bias on returns per period due to the bid-ask bounce can be measured by $(P_A - P_B)^2/(P_A + P_B)^2$, where P_A and P_B are the bid and the ask prices. The bid-ask bounce bias measure is computed in a subsample for 1983–1999, using the actual quoted spread (quoted ask – quoted bid) from quote data in TAQ and ISSM. As trades could occur between the quoted bid and quoted ask, this bias measure is likely to be overstated and will serve as an upper bound of the true bias from bid-ask bounce.

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

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

TABLE 6

Impact of Bid-Ask Bounce

Table 6 reports the average characteristics of high-DLI stocks and subsets of high-DLI stocks after further sorting on market capitalization (MKT_CAP). These characteristics include MKT_CAP, trading price at formation, return 1 month prior to (month = −1) and 1 month after (month = 1) formation, a bid-ask bounce bias measure, and first-month return computed using daily returns from the second positive trading volume-day. The bid-ask bounce bias measure is computed as $(P_A - P_B)^2/(P_A + P_B)^2$, where P_A and P_B are the bid and ask prices of the stock. The sampling period is 1971–1999. Due to the availability of TAQ data, the bid-ask bounce bias measure is computed starting from 1983.

Portfolio	MKT_CAP (millions $)	Price ($)	Return (%) Month = −1	Return (%) Month = 1	Bid-Ask Bounce Bias	Return (%) Month = 1 w/o 1st Day
High-DLI	39.6	3.58	−3.39	2.10	0.40	2.02
Portfolio	High-DLI Stocks Sorted on MKT_CAP					
Large	166.4	8.03	−2.30	0.36	0.08	0.36
2	18.4	4.06	−2.49	0.60	0.24	0.60
3	8.3	2.80	−2.43	0.84	0.40	0.91
4	4.3	1.87	−3.49	2.30	0.54	2.37
Small	1.7	1.18	−6.27	6.47	0.77	5.87

When we exclude the returns on the first trading day of the calendar month, the returns drop only slightly. For example, the first-month returns of the high-DLI stocks drop from 2.10% to 2.01%, indicating that the true impact of bid-ask bounce is small. Although the drop in the first-month returns is much higher for the smallest high-DLI stocks (from 6.47% to 5.87%), the first-month returns excluding the first trading day of 5.87% are still too high to be explained by most risk models. All this evidence seems to suggest that the random bounce between bid and ask does not fully explain the high first-month returns on the high-DLI stock portfolio.[4]

C. Investor Overreaction

The short-term return reversal we have documented for high-DLI stocks is also potentially consistent with investor overreaction, as explored in various behavioral models (e.g., De Long et al. (1990), Barberis et al. (1998), and Daniel et al. (1998)).

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

Second, Hirshleifer (2001) suggests that behavioral biases such as overconfidence should be stronger when the decision environment is more uncertain and

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

feedback is slow. Under the overreaction-based explanation, one typically would expect greater reversal for a stock associated with higher uncertainty. We examine this conjecture by looking at high-DLI losers and applying a cash-flow-based uncertainty measure developed by Zhang (2006). At the end of each month, we sort high-DLI losers into 2 portfolios according to the uncertainty measures and compute the equal-weighted portfolio return during the first month after portfolio formation for each portfolio separately. The first-month returns on the 2 portfolios are similar: 6.87% for high-DLI losers with high uncertainty measures and 7.04% for high-DLI losers with low uncertainty measures. The difference of 17 bp is not significant (t-value = 0.29). We therefore reject increased uncertainty or related investor overreaction as the primary explanation of the first-month high return on the high-DLI stock portfolio.

V. Conclusion

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

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

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

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

After accounting for the impact of short-term liquidity shock on distressed stocks, much of the recent evidence suggests that default or financially distressed risk could lead to lower stock returns. This finding presents a new puzzle, as financially distressed stocks are riskier according to standard risk measures such as return standard deviation, market beta and loadings on value, and small-cap risk factors (see Campbell, Hilscher, et al. (2008)). In addition, the relation between default risk and stock returns also depends on other factors such as the BM ratio (see Griffin and Lemmon (2002)) and shareholder advantage (see Garlappi et al. (2008)). Our findings suggest that the examination of clientele change and related trading on financially distressed securities may aid in answering questions related to the timing of distress returns.

References

Almazan, A.; K. C. Brown; M. Carlson; and D. A. Chapman. "Why Constrain Your Mutual Fund Manager?" *Journal of Financial Economics*, 73 (2004), 289–321.

Altman, E. I. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *Journal of Finance*, 23 (1968), 589–609.

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

Angel J. J.; J. H. Harris; V. Panchapagesan; and I. Werner. "From Pink Slips to Pink Sheets: Liquidity and Shareholder Wealth Consequences of Nasdaq Delistings." Working Paper, Ohio State University (2004).

Asparouhova E.; H. Bessembinder; and I. Kalcheva. "Liquidity Biases in Asset Pricing Tests." *Journal of Financial Economics*, forthcoming (2010).

Avramov, D.; T. Chordia; and A. Goyal. "Liquidity and Autocorrelations in Individual Stock Returns." *Journal of Finance*, 61 (2006), 2365–2394.

Barberis, N.; A. Shleifer; and R. Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 49 (1998), 307–343.

Berndt, A.; R. Douglas; D. Duffie; M. Ferguson; and D. Schranz. "Measuring Default Risk Premia from Default Swap Rates and EDFs." Working Paper, Stanford University (2005).

Bhandari, L. C. "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence." *Journal of Finance*, 43 (1988), 507–528.

Black, F., and M. Scholes. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy*, 81 (1973), 637–654.

Blume, M. E., and R. F. Stambaugh. "Biases in Computed Returns: An Application to the Size Effect." *Journal of Financial Economics*, 12 (1983), 387–404.

Campbell, J. Y.; S. J. Grossman; and J. Wang. "Trading Volume and Serial Correlation in Stock Returns." *Quarterly Journal of Economics*, 108 (1993), 905–939.

Campbell, J. Y.; J. Hilscher; and J. Szilagyi. "In Search of Distress Risk." *Journal of Finance*, 63 (2008), 2899–2939.

Conrad, J. S.; A. Hameed; and C. Niden. "Volume and Autocovariances in Short-Horizon Individual Security Returns." *Journal of Finance*, 49 (1994), 1305–1329.

Conrad, J.; K. M. Johnson; and S. Wahal. "Institutional Trading and Alternative Trading Systems." *Journal of Financial Economics*, 70 (2003), 99–134.

Coval, J., and E. Stafford. "Asset Fire Sales (and Purchases) in Equity Markets." *Journal of Financial Economics*, 86 (2007), 479–512.

Daniel, K.; M. Grinblatt; S. Titman; and R. Wermers. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance*, 52 (1997), 1035–1058.

Daniel, K.; D. Hirshleifer; and A. Subrahmanyam. "Investor Psychology and Security Market Under- and Overreactions." *Journal of Finance*, 53 (1998), 1839–1885.

De Long, J. B.; A. Shleifer; L. H. Summers; and R. J. Waldmann. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance*, 45 (1990), 379–395.

Dichev, I. D. "Is the Risk of Bankruptcy a Systematic Risk?" *Journal of Finance*, 53 (1998), 1131–1147.

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Friedland, D. "Distressed Securities Investing." Working Paper, Magnum Fund (2005).

Garlappi, L.; T. Shu; and H. Yan. "Default Risk, Shareholder Advantage, and Stock Returns." *Review of Financial Studies*, 21 (2008), 2743–2778.

George, T. J., and C.-Y. Hwang. "A Resolution of the Distress Risk and Leverage Puzzles in the Cross Section of Stock Returns." *Journal of Financial Economics*, forthcoming (2010).

Griffin, J. M.; J. H. Harris; and S. Topaloglu. "The Dynamics of Institutional and Individual Trading." *Journal of Finance*, 58 (2003), 2285–2320.

Griffin, J. M., and M. L. Lemmon. "Book-to-Market Equity, Distress Risk and Stock Returns." *Journal of Finance*, 57 (2002), 2317–2336.

Grossman, S., and M. H. Miller. "Liquidity and Market Structure." *Journal of Finance*, 43 (1988), 617–633.

Hansen, L. P., and R. Jagannathan. "Implications of Security Market Data for Models of Dynamic Economies." *Journal of Political Economy*, 99 (1991), 225–262.

Haugen, R. A., and J. Lakonishok. "The Incredible January Effect: The Stock Market's Unsolved Mystery." Homewood, IL: Dow Jones-Irwin (1988).

Hillegeist, S. A.; E. K. Keating; D. P. Cram; and K. G. Lundstedt. "Assessing the Probability of Bankruptcy." *Review of Accounting Studies*, 9 (2004), 5–34.

Hirshleifer, D. "Investor Psychology and Asset Pricing." *Journal of Finance*, 56 (2001), 1533–1597.

Huang, R. D., and H. R. Stoll. "Dealer versus Auction Markets: A Paired Comparison of Execution Costs on NASDAQ and the NYSE." *Journal of Financial Economics*, 41 (1996), 313–358.

Jegadeesh, N. "Evidence of Predictable Behavior of Security Returns." *Journal of Finance*, 45 (1990), 881–898.

Kaniel R.; G. Saar; and S. Titman. "Individual Investor Trading and Stock Returns." *Journal of Finance*, 63 (2008), 273–310.

Keim, D. B., and A. Madhavan. "Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders." *Journal of Financial Economics*, 37 (1995), 371–398.

Lehman, B. N. "Fads, Martingales, and Market Efficiency." *Quarterly Journal of Economics*, 105 (1990), 1–28.

Macey, J.; M. O'Hara; and D. Pompilio. "Down and Out in the Stock Market: The Law and Finance of the Delisting Process." Working Paper, Cornell University (2004).

Mech, T. S. "Portfolio Return Autocorrelation." *Journal of Financial Economics*, 34 (1993), 307–344.

Merton, R. C. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29 (1974), 449–470.

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

Ohlson, J. A. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Accounting Research*, 18 (1980), 109–131.

Shumway, T. "Forecasting Bankruptcy More Accurately: A Simple Hazard Model." *Journal of Business*, 74 (2001), 101–124.

Vassalou, M., and Y. Xing. "Default Risk in Equity Returns." *Journal of Finance*, 59 (2004), 831–868.

Zhang, X. F. "Information Uncertainty and Stock Returns." *Journal of Finance*, 61 (2006), 105–137.