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Liquidity and the Post-Earnings-Announcement Drift

Tarun Chordia, Amit Goyal, Gil Sadka, Ronnie Sadka, and Lakshmanan Shivakumar

The post-earnings-announcement drift is a long-standing anomaly that conflicts with market efficiency. This study documents that the post-earnings-announcement drift occurs mainly in highly illiquid stocks. A trading strategy that goes long high-earnings-surprise stocks and short low-earnings-surprise stocks provides a monthly value-weighted return of 0.04 percent in the most liquid stocks and 2.43 percent in the most illiquid stocks. The illiquid stocks have high trading costs and high market impact costs. By using a multitude of estimates, the study finds that transaction costs account for 70–100 percent of the paper profits from a long–short strategy designed to exploit the earnings momentum anomaly.

Fama (1998) pointed out the existence of two robust and persistent anomalies that still pose a challenge to the efficient market paradigm. One of these anomalies is the post-earnings-announcement drift (PEAD), or earnings momentum, which is the topic of our research.[1] Earnings momentum refers to the fact that companies that report unexpectedly high earnings subsequently outperform companies that report unexpectedly low earnings. Ball and Brown (1968) were the first to note that stock prices continue to drift in the direction of earnings surprises for several months after the earnings are announced. Schwert (2003) showed that a number of market anomalies have typically disappeared, reversed, or attenuated following their discovery. The post-earnings-announcement drift, together with price momentum, is still robust after its initial discovery; several studies have confirmed the robustness of the PEAD, or earnings momentum, by using both more recent data[2] and data from stock markets outside the United States, where the phenomenon was first identified.

Tarun Chordia is the R. Howard Dobbs Chair in Finance and Amit Goyal is associate professor of finance at Goizueta Business School, Emory University, Atlanta. Gil Sadka is assistant professor of accounting at Columbia Business School, Columbia University, New York City. Ronnie Sadka is associate professor of finance at Carroll School of Management, Boston College. Lakshmanan Shivakumar is the London Business School Chaired Professor of Accounting at London Business School.

Commonly interpreted as evidence that investors underreact to earnings surprises, the PEAD is thus inconsistent with market efficiency and investor rationality (see Ball and Bartov 1996). Chordia and Shivakumar (2006) documented that a portfolio long in stocks with the highest earnings surprises and short in stocks with the lowest earnings surprises provides a monthly return of 90 bps, or more than 10 percent annually. In efficient markets, simple long–short trading strategies should not be profitable. Such large profits over a period of almost four decades point to a violation of the semi-strong-form market efficiency as defined by Fama (1970).

In this article, we attempt to answer the following question: Why have the profits from an earnings momentum strategy been robust over a period of four decades?[3] Exploring the notion that potential profits from the PEAD may not be realizable because of trading frictions, we introduced such frictions in the form of trading costs to evaluate the profitability of trading strategies that exploit the drift. More specifically, because the PEAD is prevalent mainly in stocks that are relatively illiquid, we examined the impact of illiquidity on the trading profits. Although liquidity is an elusive concept, most market participants agree that liquidity generally reflects the ability to quickly buy or sell sufficient quantities at low trading cost and without having a significant impact on the market price. Following Amihud (2002), we measured monthly illiquidity as the average of the daily price impacts of the order flow (i.e., the daily absolute price change per dollar of daily trading volume). We examined the profitability of the long–short strategy after sorting stocks into decile portfolios on the basis of this illiquidity measure.

But the long–short trading strategy that attempts to profit from the PEAD generates high transaction costs and substantial price impact. Specifically, we used the transaction-cost estimates of Keim and Madhavan (1997), Hanna and Ready (2005), Korajczyk and Sadka (2004), and Chen, Stanzl, and Watanabe (2004) to estimate net returns on the basis of a strategy that buys the high-earnings-surprise stocks and sells the low-earnings-surprise stocks.

Although we are not the first to suggest that transaction costs could be related to the PEAD, we provide the first detailed examination of trading costs by using high-frequency transaction data. Bhushan (1994) documented that the drift is stronger for smaller, low-priced stocks. Brav and Heaton (2006) also found that drift is stronger for the smaller stocks. Hou and Moskowitz (2005) showed that the PEAD is prevalent in stocks that have the most friction as measured by the delay by which their prices adjust to information. Mendenhall (2004) suggested that stocks with high arbitrage risk, proxied by idiosyncratic volatility, exhibit more drift than do stocks with low arbitrage risk. Although all these studies suggest a transaction-cost explanation for the persistence of the earnings drift, none provide a detailed and direct examination of transaction costs.

Two recent papers address high-frequency data. Battalio and Mendenhall (2007) examined the impact of bid–ask spreads on the profitability of a PEAD strategy and found that the long–short strategy continues to be profitable. Ng, Rusticus, and Verdi (2008) also studied bid–ask spreads (as well as commissions) and found that the returns of the PEAD strategy are significantly reduced (although not eliminated). Neither team, however, examined market impact costs and short-sale costs, which are likely to be the main trading costs for informed institutional traders. Moreover, the results in Battalio and Mendenhall (2007) arose from event-based strategies likely to incur high transaction costs owing to frequent portfolio rebalancing. Thus, these papers underestimate the implications of transaction costs for the profitability of a PEAD trading strategy. The use of high-frequency data to measure market impact costs is important because it enables the precise quantification of the post-transaction-cost profitability of earnings momentum strategies.

Our article is also related to a recent strand in the literature that reexamines market anomalies in the context of transaction costs. For instance, Korajczyk and Sadka (2004) studied the impact of transaction costs on price momentum strategies. Avramov, Chordia, and Goyal (2006) showed that the short-run reversal strategies at the weekly and monthly frequencies are not profitable once transaction costs are taken into account. Hanna and Ready (2005) found that the Haugen and Baker (1996) trading strategies do not provide attractive returns after accounting for transaction costs. Brav and Heaton (2006) showed that the poor returns for small growth stocks occur in less than 1 percent of the market value of the CRSP universe of U.S. common stocks, where the transaction costs are likely to be high. Our contribution is to provide a detailed examination of transaction costs that could inhibit prices from adjusting completely and quickly to earnings information.

Although the presence of statistically significant earnings momentum in individual security returns is undeniable, profiting from this predictability is impossible. This lack of profitability is consistent with Jensen's (1978) definition of market efficiency and Rubinstein's (2001) definition of minimally rational markets.[4] The lack of profitability from a long–short strategy that exploits earnings momentum suggests that the violations of the efficient market hypothesis arising from the PEAD are not so egregious after all.

Data

Our sample consists of all NYSE and Amex companies with data available on the monthly CRSP and quarterly Standard & Poor's Compustat files for the period January 1972 through December 2005. We focused on common stocks only and eliminated from the sample American Depositary Receipts, REITs, American trust components, units, and closed-end funds. To avoid the extremely illiquid securities, we also eliminated from the sample all stocks priced below \$5.00 at the start of each month.[5] The average number of stocks in the sample is 1,838.

We used standardized unexpected earnings (SUE) to capture the PEAD. We computed a company's SUE as the most recently announced quarterly earnings less the earnings four quarters earlier. This earnings change is standardized by its standard deviation estimated over the previous eight quarters. Specifically, SUE is calculated as

$$\text{SUE}_{it} = \frac{E_{iq} - E_{iq-4}}{\sigma_{iq}}, \tag{1}$$

where E_{iq} is the most recent earnings for quarter q announced in month t and σ_{iq} is the standard deviation of $(E_{iq} - E_{iq-4})$ over the previous eight quarters.

The Amihud (2002) illiquidity measure is the average daily price impact of order flow and is computed as the absolute price change per dollar of daily trading volume:

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{t=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6, \quad (2)$$

where R_{itd} is the daily return, $DVOL_{itd}$ is the dollar trading volume of stock i on day d in month t, and D_{it} is the number of days in month t for which data are available for stock i. We computed the Amihud illiquidity measure at the monthly frequency. We required at least 10 days of trades per month for each stock. Hasbrouck (2003) compared effective and price-impact measures estimated from daily data with those estimated from high-frequency data and found that the Amihud measure is the most highly correlated with trade-based measures. To check for robustness, we conducted all our tests with an alternative measure of liquidity proposed by Liu (2006) and found essentially the same results as those reported in that article.

Results

Table 1 presents equal-weighted and value-weighted illiquidity and returns for SUE-sorted decile portfolios. For each month, sample companies are sorted into deciles on the basis of the most recent SUE. The break points for sorting on SUE are determined by the distribution of SUE computed in months $t - 2$ to t. The SUE-sorted portfolios are held for the subsequent three months. We followed Jegadeesh and Titman (1993) in forming decile portfolios to avoid test statistics based on overlapping returns. With a three-month holding period, each monthly measure is an equal-weighted average of the equal- or value-weighted ranking portfolio formed for each of the past three months.

On average, companies with positive earnings surprises are more liquid than companies with negative earnings surprises, possibly because of more information asymmetry and/or uncertainty among "bad news" companies (see Hayn 1995). For instance, the equal-weighted (value-weighted) Amihud illiquidity measure is 0.836 (0.104) for the lowest-SUE portfolio and 0.571 (0.054) for the highest-SUE portfolio. Our results regarding the liquidity level of SUE portfolios, however, do not explain the existence of the anomaly. To the extent that liquidity level carries a premium, one would expect low-liquidity companies to have higher expected returns than high-liquidity companies.

Table 1. SUE-Sorted Portfolios, 1972–2005

	Equal Weighted		Value Weighted	
Portfolio	Illiquidity	Return	Illiquidity	Return
1	0.836	0.622%	0.104	1.089%
2	0.964	0.782	0.187	0.941
3	0.915	0.766	0.133	0.848
4	0.918	0.963	0.107	0.809
5	0.858	1.062	0.112	1.040
6	0.801	1.218	0.095	1.113
7	0.773	1.452	0.085	0.974
8	0.719	1.646	0.082	1.302
9	0.731	1.766	0.078	1.270
10	0.571	1.936	0.054	1.507
10–1	0.703	1.314	0.079	0.418
10–1 alphas from factor models				
1-Factor		1.33%		0.49%
		(10.02)		(3.11)
3-Factor		1.42%		0.55%
		(9.10)		(3.41)
4-Factor		1.18%		0.25%
		(7.63)		(1.56)
5-Factor		1.22%		0.42%
		(6.62)		(2.58)

Notes: This table presents illiquidity and returns of SUE-sorted portfolios. The table also reports alphas for the hedge portfolio that is long the highest-SUE portfolio and short the lowest-SUE portfolio. The alphas' t-statistics are reported in parentheses.

But our results indicate the opposite phenomenon: The high-SUE companies are more liquid than the low-SUE companies, yet high-SUE companies outperform low-SUE companies.

The average equal-weighted monthly returns (computed for a three-month holding period) vary almost monotonically, from 0.62 percent per month for the lowest-SUE portfolio to 1.94 percent for the highest-SUE portfolio. The difference in the monthly returns between the two extreme decile portfolios is 1.31 percent. Thus, the PEAD strategy of going long the high-SUE stocks and going short the low-SUE stocks results in equal-weighted returns of about 3.9 percent over the following three months. The monthly alpha is a statistically significant 1.33 percent for the market model and 1.42 percent for the Fama and French (1993) model. When the Fama–French factors are augmented with a price-momentum-based factor, UMD, the alpha is 1.18 percent per month.

Given that the SUE portfolios differ in their levels of liquidity, one might well ask whether the loading on a liquidity risk factor explains these long–short portfolio returns. Thus, we also augmented the Fama–French factors with both UMD and the Pástor and Stambaugh (PS 2003) liquidity factor. The risk-adjusted long–short portfolio alpha is 1.22 percent when using the Fama–French factors along with UMD and the PS traded-liquidity factor. Moreover, the beta on PS of the long–short SUE portfolio is insignificant. These findings suggest that although high-SUE companies are more liquid in *levels* than are low-SUE companies, they are not more sensitive to liquidity *risk*. Therefore, the standard asset-pricing models do not capture the profits from an earnings momentum strategy.[6]

The value-weighted monthly returns, however, provide a return differential between the two extreme decile portfolios of only 0.42 percent per month, which is much lower than that of the equal-weighted long–short strategy (1.31 percent). This finding suggests that a large portion of the returns from the PEAD strategy is obtained from the smaller and presumably less liquid stocks.

Table 2 presents the average monthly returns of portfolios that are sorted independently on SUE and illiquidity. Once again, the returns are computed for a three-month period after the formation of the SUE- and illiquidity-sorted portfolios. The returns are value weighted within each of the 100 portfolios, which are 10 × 10 sorted on SUE and illiquidity. Because the portfolios in Table 2 are formed by sorting stocks independently on SUE and illiquidity, one might well ask whether the various portfolios are well populated. We checked to ensure that all the portfolios were well populated and that the results were not being driven by outliers.[7]

The monthly returns of these portfolios generally increase with SUE. For instance, for the most illiquid portfolio, the returns increase from –0.05 percent for the lowest-SUE portfolio to 2.39 percent for the highest-SUE portfolio. Returns increase (decrease) with illiquidity for the high-SUE (low-SUE) stocks. For the lowest-SUE portfolio, returns decrease from 1.25 percent for the most liquid stocks to –0.05 percent for the most illiquid stocks. For the highest-SUE portfolio, however, returns increase from 1.29 percent for the most liquid stocks to 2.39 percent for the most illiquid stocks. These findings are consistent with a concentration in the illiquid stocks of underreaction to bad news in the lowest-SUE portfolio and to good news in the highest-SUE portfolio.

Given that the returns of the lowest-SUE portfolio decrease with illiquidity and those of the highest-SUE portfolio increase with illiquidity, the difference in returns between the highest-SUE portfolio and the lowest-SUE portfolio increases with illiquidity. For the most liquid stocks, this difference is only 0.04 percent per month, but for the most illiquid stocks, the difference is 2.43 percent. These findings show that the profits from a strategy that exploits the PEAD by buying the high-SUE stocks and selling the low-SUE stocks are higher for the more illiquid stocks. The PEAD strategy profits increase nonlinearly with illiquidity, and this increase could be related to the nonlinear increase in transaction costs. These findings are also consistent with Bartov, Radhakrishnan, and Krinsky (2005), who showed that the PEAD is negatively correlated with institutional ownership. In general, stocks with high institutional ownership are more liquid than those with low institutional ownership.

The alphas from various factor models for the long–short SUE portfolios are highly significant for the more illiquid stocks. For the low-SUE stocks, the alpha from the Fama–French (1993) model decreases from 0.31 percent per month for the most liquid stocks to –1.41 percent for the most illiquid stocks. For the high-SUE stocks, the Fama–French alpha increases from 0.43 percent to 1.03 percent. When the Fama–French model is augmented with a factor for momentum (UMD), the highly illiquid low-SUE stocks have a monthly alpha of –1.24 percent and the highly illiquid high-SUE stocks have an alpha of 1.19 percent. For the highly illiquid stocks, the low-SUE alphas are larger in absolute value than the high-SUE alphas, which suggests that a large fraction of the PEAD is a negative-earnings-surprise phenomenon. In other words, the drift that follows the negative earnings surprise results in a large fraction of payoffs from the earnings momentum strategies.

Table 2. Gross Returns of SUE- and Illiquidity-Sorted Portfolios, 1972–2005

	Most Liquid									Most Illiquid
SUE Rank	1	2	3	4	5	6	7	8	9	10
Gross returns										
1	1.25%	1.28%	0.81%	0.84%	1.21%	0.81%	0.77%	0.43%	–0.10%	–0.05%
2	1.13	0.89	1.18	1.20	0.91	0.72	1.20	0.87	1.05	0.32
3	0.72	1.36	0.96	1.01	0.76	1.03	1.08	1.02	0.61	0.24
4	0.70	1.09	0.94	0.91	0.89	0.86	0.89	0.96	0.93	1.21
5	1.01	1.19	1.01	0.92	0.86	1.24	0.96	1.28	1.23	1.09
6	1.07	0.86	0.98	1.18	1.38	0.90	1.51	1.36	1.28	1.33
7	0.82	0.94	1.39	1.37	1.33	1.28	1.53	1.82	1.95	1.75
8	1.17	1.51	1.29	1.31	1.53	1.43	2.05	1.86	2.14	2.44
9	1.10	1.33	1.35	1.27	1.52	1.57	1.85	2.28	2.22	2.31
10	1.29	1.94	1.68	1.81	1.95	2.05	1.76	2.66	2.40	2.39
10−1	0.04	0.66	0.87	0.97	0.74	1.23	0.99	2.23	2.50	2.43
3-Factor alphas										
1	0.31%	0.00%	–0.47%	–0.51%	–0.26%	–0.67%	–0.63%	–0.93%	–1.55%	–1.41%
	(1.50)	(0.02)	(–2.46)	(–2.23)	(–1.29)	(–2.60)	(–2.36)	(–5.43)	(–6.85)	(–5.05)
10	0.43%	0.77%	0.54%	0.63%	0.67%	0.72%	0.44%	1.39%	0.92%	1.03%
	(3.08)	(3.73)	(2.79)	(2.64)	(2.64)	(3.17)	(1.85)	(4.47)	(3.06)	(4.58)
10−1	0.12%	0.77%	1.01%	1.13%	0.94%	1.40%	1.07%	2.32%	2.47%	2.44%
	(0.47)	(2.43)	(4.13)	(3.76)	(3.21)	(4.07)	(3.18)	(6.57)	(6.18)	(9.06)
4-Factor alphas										
1	0.41%	0.20%	–0.23%	–0.43%	–0.08%	–0.46%	–0.45%	–0.81%	–1.39%	–1.24%
	(1.90)	(1.00)	(–1.31)	(–2.10)	(–0.38)	(–1.94)	(–1.75)	(–4.16)	(–6.47)	(–5.04)
10	0.26%	0.66%	0.43%	0.63%	0.71%	0.68%	0.45%	1.34%	0.90%	1.19%
	(1.72)	(3.27)	(2.21)	(2.71)	(3.24)	(2.98)	(2.22)	(4.31)	(2.76)	(5.48)
10−1	–0.16%	0.47%	0.66%	1.05%	0.79%	1.14%	0.90%	2.15%	2.29%	2.43%
	(–0.57)	(1.48)	(2.64)	(3.11)	(2.83)	(3.18)	(2.56)	(5.99)	(5.40)	(9.69)

Notes: This table presents the time-series averages of the mean gross returns of value-weighted SUE- and illiquidity-sorted portfolios. It also reports alphas, whose Newey–West *t*-statistics are reported in parentheses.

For the most illiquid long–short SUE portfolio, we also found that the alpha from the market model is 2.43 percent (unreported in the table); from the Fama–French model, 2.44 percent; and from the Fama–French model augmented with UMD, 2.43 percent. Because conditioning on illiquidity has a large impact on the gross returns to the SUE portfolios, we again calculated long–short alpha from the Fama–French model augmented with both UMD and the PS liquidity factor and found that it is still significant, at 2.37 percent (unreported in the table), for the most illiquid portfolio.

Because Daniel and Titman (1997) suggested that company characteristics—not the factor loadings—affect the cross-section of stock returns, we computed the characteristic-adjusted returns for the SUE- and illiquidity-sorted portfolios in Table 2 (unreported results available upon request). Individual stock returns are adjusted by subtracting the matching size and book-to-market portfolio returns from gross returns, and the value-weighted averages of these individual stock returns are computed to obtain the SUE- and illiquidity-sorted portfolio returns. For the most illiquid stocks, the characteristic-adjusted returns for the low-SUE stocks are –1.55 percent per month; for the most illiquid high-SUE stocks, they are 0.89 percent. Once again, these results suggest that the drift in the low-SUE stocks is larger (twice as large in the case of characteristic-adjusted returns) than the drift in the high-SUE stocks. The long–short characteristic-adjusted portfolio returns increase monotonically from 0.02 percent per month for the most liquid stocks to 2.44 percent for the most illiquid stocks.

Cross-Sectional Tests. By using cross-sectional asset-pricing tests with individual stocks rather than portfolios, we confirmed that illiquidity has an important impact on the post-earnings-announcement drift. Our asset-pricing tests extend the approach of Brennan, Chordia, and Subrahmanyam (BCS 1998). BCS tested factor models by regressing risk-adjusted returns on such company-level attributes as size, book-to-market, and turnover. Under the null of exact pricing, such attributes should be statistically insignificant in the cross-section. This approach avoids the data-snooping biases that are inherent in portfolio-based approaches (see Lo and MacKinlay 1990), and the use of individual stocks as test assets is robust to the sensitivity of asset-pricing tests to the portfolio grouping procedure.

We ran the following cross-sectional Fama and MacBeth (1973) regression of risk-adjusted returns on company characteristics:

$$R_{jt} - R_{ft} - \sum_{k=1}^{K} \hat{\beta}_{jk} F_{kt} = c_{ot} + \sum_{m=1}^{M} c_{mt} Z_{mjt-2} + e_{jt}, \qquad (3)$$

where $\hat{\beta}_{jk}$ is the beta estimated by a first-pass time-series regression of the company's stock return on the Fama and French (1993) factors over the entire sample period with nonmissing returns data,[8] Z_{mjt} is the value of characteristic m for security j at time t, and M is the total number of characteristics. We report the time-series averages of these coefficients, c_t. The standard errors of these estimators are obtained from the time series of monthly estimates and are corrected for errors in variables following Shanken (1992).

The company characteristics are as follows:

1. Sz: size, measured as the natural logarithm of the market value of equity;
2. BtoM: natural logarithm of the ratio of book value of equity to market value of equity, calculated following Fama and French (1992);
3. DVol: natural logarithm of the dollar volume of trading;
4. Ret12: cumulative return over the last 12 months;
5. SUE: standardized unexpected earnings, measured as in Table 1;
6. Illiq: natural logarithm of the Amihud illiquidity measure, computed on the basis of the ratio of absolute returns to dollar volume; and
7. IdioVol: idiosyncratic volatility, calculated for each stock for each month as the sum of the squared residuals from a regression of the daily excess stock returns on the daily excess market returns.

All the characteristics are lagged by two months relative to the month in which the dependent variable is measured.

The results are presented in **Table 3**. The first regression essentially repeats results in BCS. Company characteristics matter: Small stocks, high-book-to-market stocks, stocks with low dollar trading volume, and stocks with high past-12-month returns all have higher risk-adjusted returns. The second regression shows that the coefficient on SUE is positive and highly significant, which suggests that stocks with high earnings surprises have higher average returns than do stocks with low earnings surprises**.** With SUE as one of the dependent variables, the coefficient on the past-12-month returns declines and becomes statistically insignificant at the 5 percent level (see Chordia and Shivakumar 2006).

The third regression introduces an interaction term of company size and SUE. The coefficient on the interaction term is significantly negative, which suggests that small companies exhibit more earnings momentum than do large companies.[9] In the fourth regression, we introduced an interaction term of SUE and the Amihud illiquidity measure. The coefficient on this interaction term is significantly positive, which suggests that the impact of SUE on risk-adjusted returns is higher for the more illiquid stocks.

Table 3. Cross-Sectional Regressions

	CNST	Sz	BtoM	DVol	Ret12	SUE	SUE*Sz	SUE*Illiq	SUE*IdioVol
1.	0.230	0.063	0.168	–0.112	0.774				
	(0.50)	(1.14)	(3.80)	(–2.72)	(6.17)				
2.	1.581	–0.109	0.176	–0.034	0.769	0.128			
	(2.61)	(–1.42)	(2.49)	(–0.59)	(4.70)	(6.63)			
3.	1.569	–0.101	0.185	–0.041	0.728	0.919	–0.064		
	(2.57)	(–1.32)	(2.62)	(–0.71)	(4.44)	(5.75)	(–4.97)		
4.	1.571	–0.101	0.189	–0.042	0.753	0.262		0.041	
	(2.58)	(–1.32)	(2.67)	(–0.73)	(4.61)	(7.65)		(4.70)	
5.	1.452	–0.091	0.181	–0.046	0.763	0.109			0.003
	(2.41)	(–1.20)	(2.59)	(–0.80)	(4.63)	(4.74)			(1.91)

Notes: This table reports the time-series averages of the coefficients obtained from Equation 3. The *t*-statistics of these estimators are reported in parentheses.

Mendenhall (2004) argued that arbitrage risk, as proxied by idiosyncratic volatility, inhibits arbitrageurs from exploiting the earnings drift, and therefore, stocks with higher idiosyncratic volatility exhibit higher earnings drift. In examining this hypothesis, we tested whether the interaction term of idiosyncratic volatility and SUE is an important determinant of the cross-section of returns. The coefficient on this interaction term is statistically insignificant at the 5 percent level in the fifth and sixth regressions, which suggests that idiosyncratic volatility does not affect the cross-section of returns beyond the impact of company size or liquidity. Thus, contrary to the results in Mendenhall (2004), idiosyncratic volatility does not drive the post-earnings-announcement drift.[10]

Overall, the post-earnings-announcement drift is prevalent mainly in illiquid companies. Company size also affects the drift, but that effect could occur because size proxies for illiquidity. The impact of idiosyncratic volatility on returns is subsumed by that of size and illiquidity.

Characteristics of Illiquidity-Sorted Portfolios. Table 4 presents descriptive statistics for the various two-way-sorted portfolios in Table 2. Company characteristics are averaged over the three-month holding period after the portfolio formation date. For each calendar month, the value-weighted company characteristics for each portfolio are obtained among the stocks in that portfolio. The table presents the time-series averages of the cross-sectional value-weighted averages. The company characteristics are illiquidity, turnover, dollar trading volume, decile size rank (based on NYSE break points), idiosyncratic volatility, institutional ownership, quoted depth, and the proportional quoted and effective spreads for each portfolio (respectively, PQSPR and PESPR). The proportional quoted depth is the difference between the ask and bid prices divided by the midpoint of the spread. The proportional effective spread is defined as twice the absolute value of the difference between the transaction price and the quote midpoint divided by the quote midpoint. The quoted depth represents the number of shares offered for trade at the inside bid and ask quotes. In general, the characteristics are computed for the period 1972–2005. But institutional ownership is for 1980–2005, and the spreads and quoted depths are obtained from the Institute for the Study of Security Markets database and Trade and Quote database for 1988–2005 for NYSE stocks only.[11]

Table 4. Company Characteristics of SUE- and Illiquidity-Sorted Portfolios, 1972–2005

	Most Liquid				Most Illiquid	Most Liquid				Most Illiquid
SUE Rank	1	3	5	7	10	1	3	5	7	10
	SzRank					Illiquidity				
1	9.4	7.3	5.2	3.4	1.3	0.005	0.047	0.131	0.385	3.701
5	9.6	7.3	5.4	3.4	1.3	0.006	0.034	0.119	0.378	3.312
10	9.4	7.4	5.3	3.5	1.3	0.003	0.031	0.122	0.345	3.155
	Turnover					DVol				
1	6.5%	7.1%	6.1%	4.4%	1.9%	1,413.4	127.4	40.1	12.9	0.8
5	6.3	7.0	5.4	4.3	1.9	1,360.8	127.8	41.2	13.9	0.9
10	6.4	7.7	6.2	4.5	2.3	1,515.3	130.7	44.9	14.8	1.0
	IdioVol					InstOwn				
1	8.3%	9.9%	11.5%	12.3%	13.1%	54.5%	53.1%	45.9%	39.2%	19.1%
5	7.9	9.6	10.2	11.6	12.6	54.1	55.1	46.6	39.7	20.0
10	7.5	9.4	10.1	10.9	12.7	54.8	56.1	47.5	37.4	17.8
	PESPR					PQSPR				
1	0.20%	0.37%	0.53%	0.75%	1.59%	0.29%	0.56%	0.78%	1.12%	2.40%
5	0.20	0.36	0.51	0.73	1.62	0.29	0.54	0.76	1.10	2.49
10	0.17	0.33	0.44	0.66	1.63	0.25	0.49	0.67	1.00	2.40
	Depth									
1	8.3	5.3	3.7	2.3	1.8					
5	8.3	5.1	3.9	2.6	1.7					
10	6.1	4.5	2.7	2.2	1.8					

Notes: DVol is measured in millions of dollars. Depth is measured in thousands of shares.

The results show that although the company characteristics do not change much with SUE, they vary considerably with illiquidity. Holding SUE constant, company size, institutional ownership, turnover, and dollar trading volume all decrease with illiquidity. For instance, among the high-SUE stocks, average dollar trading volume (turnover) decreases from $1.5 billion per month (6.4 percent) for the most liquid stocks to $1.0 million (2.3 percent) for the most illiquid stocks. The average decile size rank (calculated with NYSE break points) also decreases monotonically from 9.4 to 1.3. For the high-SUE portfolio, institutional ownership decreases from 55 percent for the most liquid stocks to 18 percent for the most illiquid. This finding is important because D'Avalio (2002) suggested that low institutional ownership makes short selling difficult because of problems in borrowing shares. Idiosyncratic volatility increases monotonically with illiquidity from 7 percent for the most liquid stocks to 13 percent for the most illiquid stocks. Both the proportional effective spread and the proportional quoted spread increase with illiquidity; depth decreases with illiquidity. For example, for the high-SUE stocks, the proportional effective (quoted) spread increases from 0.17 percent (0.25 percent) for the most liquid stocks to 1.63 percent (2.40 percent) for the most illiquid stocks; the quoted depth decreases from 6,100 to 1,800 shares. Note that the spreads increase nonlinearly with illiquidity.

To summarize, even after adjusting for the standard risk factors and company characteristics, the long–short portfolio returns are well in excess of 2 percent per month. These excess returns, however, are obtained with the highly illiquid stocks only (Table 2). The fact that the PEAD strategy profits are confined to the most illiquid stocks suggests that these profits may not be easily realizable, because the illiquid stocks have high transaction costs, high market impact costs, low trading volume, and low quoted depths (Table 4).

Transaction Costs

An examination of the effective spreads in Table 4 amplifies the suspicion that transaction costs may render any trading strategy unprofitable. The proportional bid–ask spread of the highly illiquid stocks with the lowest (highest) SUE is 1.59 percent (1.63 percent). Thus, the total round-trip cost of the long–short position is 3.22 percent. The potential profit is 2.43 percent per month, or 7.3 percent over three months. Thus, the bid–ask spreads account for about 44 percent of the potential profits of the post-earnings-announcement drift. But this estimate does not take into account market impact costs, commissions, or short-sale costs. Therefore, the proportional spread of 3.22 percent may be an understatement and a more precise estimation of the trading costs is warranted.

We explicitly examined institutional transaction costs by conducting the analysis to replicate the real-time trading experience of an investor trying to exploit the earnings drift anomaly. We used the institutional transaction-cost estimates of Hanna and Ready (HR 2005), Keim and Madhavan (KM 1997), Korajczyk and Sadka (KS 2004), and Chen, Stanzl, and Watanabe (CSW 2004). Appendix A provides a short description of the features of these studies that are relevant to our analysis.

Note that even though the long–short portfolios are formed at the monthly frequency, all our transaction costs are estimated by using high-frequency data. Moreover, the cost estimates from high-frequency data have been calculated for a sample period smaller than our sample period. For instance, KM estimated costs from institutional trades for 1991–1993, but the earnings momentum profits are calculated for 1972–2005. Trading costs are likely to be higher during the early part of the sample. We conducted the analysis of trading costs by using the methodology in Cooper, Gutierrez, and Marcum (2005). Details are provided in Appendix A. Net returns after accounting for transaction costs are reported in **Table 5**.

KM Estimates. Consider the portfolio that has the most illiquid stocks and the lowest SUE. From Table 2, the gross average monthly return of this portfolio is –0.05 percent. After adjusting for the KM cost estimates of 0.80 percent, the net monthly return is –0.85 percent. Similarly, the most illiquid high-SUE portfolio has a gross average monthly return of 2.39 percent; with cost estimates of 0.75 percent, the net return is 1.64 percent. The raw returns for the high-SUE minus the low-SUE portfolio decline from 2.43 percent in Table 2 to 0.88 percent after adjusting for transaction costs of 1.55 percent (0.80 percent + 0.75 percent). Transaction costs amount to about 64 percent of the potential profits. In Table 2, the potential profits from the long–short SUE portfolios range from 0.04 percent to 2.43 percent. After accounting for transaction costs, the profits range from 0.02 percent to 0.88 percent. Thus, although the profits seem large on paper, a significant fraction of those profits is not realizable.

Note that we have been quite conservative in estimating these costs. The costs may even be further understated because KM used data for consummated trades. If some trades were abandoned because of high transaction costs, the KM estimates of trading costs would be biased downward. The

Table 5. Net Returns of SUE- and Illiquidity-Sorted Portfolios, 1972–2005

	Most Liquid				Most Illiquid	Most Liquid				Most Illiquid
SUE Rank	1	3	5	7	10	1	3	5	7	10
	Net of HR Costs					Net of KM Costs				
1	1.13%	0.61%	0.94%	0.39%	–0.73%	1.23%	0.70%	1.00%	0.39%	–0.85%
5	0.88	0.80	0.59	0.60	0.43	0.99	0.90	0.65	0.59	0.34
10	1.21	1.51	1.71	1.44	1.71	1.29	1.62	1.80	1.49	1.64
10–1	–0.16	0.49	0.23	0.29	1.07	0.02	0.69	0.37	0.34	0.88
	Net of KS Costs					Net of CSW Costs				
1	1.11%	0.48%	0.81%	0.26%	–0.88%	1.07%	0.50%	0.83%	0.16%	–1.52%
5	0.86	0.71	0.47	0.48	0.34	0.82	0.68	0.47	0.36	–0.33
10	1.19	1.43	1.60	1.33	1.45	1.15	1.40	1.57	1.17	0.79
10–1	–0.19	0.29	–0.01	0.05	0.66	–0.27	0.27	–0.03	–0.22	–0.65

Notes: This table presents mean returns, net of estimated transaction costs, for SUE- and illiquidity-sorted portfolios. The dollar amount of trading for KS and CSW estimates is $1 million.

transaction-cost estimates in KM do not include short-selling costs, and because transaction costs have been estimated for a zero-trade size, our analysis (using these estimates) has abstracted from market impact costs. Any meaningful trade size will be accompanied by substantial market impact costs.

HR Estimates. Table 5 shows that the raw returns for the high-SUE minus the low-SUE portfolio decline from 2.43 percent in Table 2 to 1.07 percent after adjusting for transaction costs of 0.68 percent. Thus, the effective spreads account for 56 percent of the paper profits. Note that the HR estimates do not account for market impact costs, commissions, or short-sale costs.

KS Estimates. We used KS estimates of market impact costs to compute the cost of establishing positions in the different illiquidity/SUE portfolios each month. We present results for $1 million of a long position and $1 million of a short position for each month.[12] Table 5 shows that after adjusting for market impact costs, net returns are significantly lower than gross returns for the long–short strategy. For the highest-illiquidity portfolio, the net returns for a long–short strategy are 0.66 percent per month. Thus, a long–short position as small as $1 million has enough market impact costs to eliminate 73 percent of the potential profits from a strategy that exploits the PEAD. Even KS estimates may understate the true transaction costs because they do not account for commissions or short-sale costs.

CSW Estimates. We used CSW estimates to measure the market impact costs for $1 million of a long position and $1 million of a short position for each month. Again, the results in Table 5 suggest that nonlinear market impact costs have a substantial impact on the net returns of the long–short SUE strategy. The average net returns are negative. For the most illiquid stocks, the net return for the long–short strategy is –0.65 percent per month. Once again, CSW's market impact cost estimates may understate the total trading costs because they do not account for commissions or short-selling costs.

Subsample Analysis. Trading costs have declined over time. Chordia, Roll, and Subrahmanyam (2001) documented a steady decrease in bid–ask spreads over time. Therefore, we explored the profitability of long–short SUE portfolios for two periods in our sample: 1972–1988 and 1989–2005. **Table 6** presents the results for the long–short portfolios. Costs have indeed declined substantially over the two subperiods. For instance, during 1972–1988, the KM trading costs for a long–short position range from 0.03 percent per month for the most liquid stocks to 1.73 percent for the most illiquid stocks. For 1989–2005, the KM trading costs are lower, ranging from 0.01 percent for the most liquid stocks to 1.38 percent for the most illiquid stocks. A similar pattern exists for the HR, KS, and CSW trading-cost estimates. For the most illiquid stocks, the HR (KS) [CSW] estimates of costs declined from 1.54 percent (1.59 percent) [3.11 percent] for 1972–1988 to 1.20 percent (1.95 percent) [3.05 percent] for 1989–2005.

Although the costs have declined over time, the potential profitability of the PEAD has also declined. Over the 1972–88 period, the gross returns ranged from 0.25 percent for the most liquid stocks to 2.74 percent for the most illiquid stocks. Over the 1989–2005 period, the corresponding returns ranged from –0.16 percent to 2.14 percent. After controlling for transaction costs, the net profitability is sometimes higher for the latter half

Table 6. Returns of SUE- and Illiquidity-Sorted Portfolios: Subsample Analysis, 1972–2005

	Most Liquid				Most Illiquid
	1	3	5	7	10
A. 1972–1988					
Gross return	0.25%	1.21%	1.18%	1.57%	2.74%
Costs (HR)	0.29%	0.53%	0.72%	0.92%	1.54%
Costs (KM)	0.03	0.23	0.48	0.77	1.73
Costs (KS)	0.29	0.61	0.79	0.95	1.59
Costs (CSW)	0.31	0.59	0.80	1.34	3.11
Net return (HR)	–0.03%	0.69%	0.46%	0.64%	1.20%
Net return (KM)	0.22	0.98	0.70	0.79	1.01
Net return (KS)	–0.03	0.60	0.39	0.61	1.15
Net return (CSW)	–0.05	0.62	0.38	0.23	–0.37
B. 1989–2005					
Gross return	–0.16%	0.53%	0.31%	0.43%	2.14%
Costs (HR)	0.12%	0.23%	0.30%	0.48%	1.20%
Costs (KM)	0.01	0.12	0.25	0.54	1.38
Costs (KS)	0.18	0.54	0.71	0.94	1.95
Costs (CSW)	0.32	0.61	0.73	1.08	3.05
Net return (HR)	–0.28%	0.30%	0.00%	–0.05%	0.94%
Net return (KM)	–0.17	0.41	0.06	–0.11	0.76
Net return (KS)	–0.34	–0.01	–0.40	–0.51	0.19
Net return (CSW)	–0.48	–0.08	–0.43	–0.65	–0.91

Notes: This table presents the results of a subsample analysis of returns, net of transaction-cost estimates, for SUE- and illiquidity-sorted portfolios. The costs and returns are shown for a hedge portfolio that comprises only stocks in the most illiquid decile and is long the highest-SUE decile and short the lowest-SUE decile.

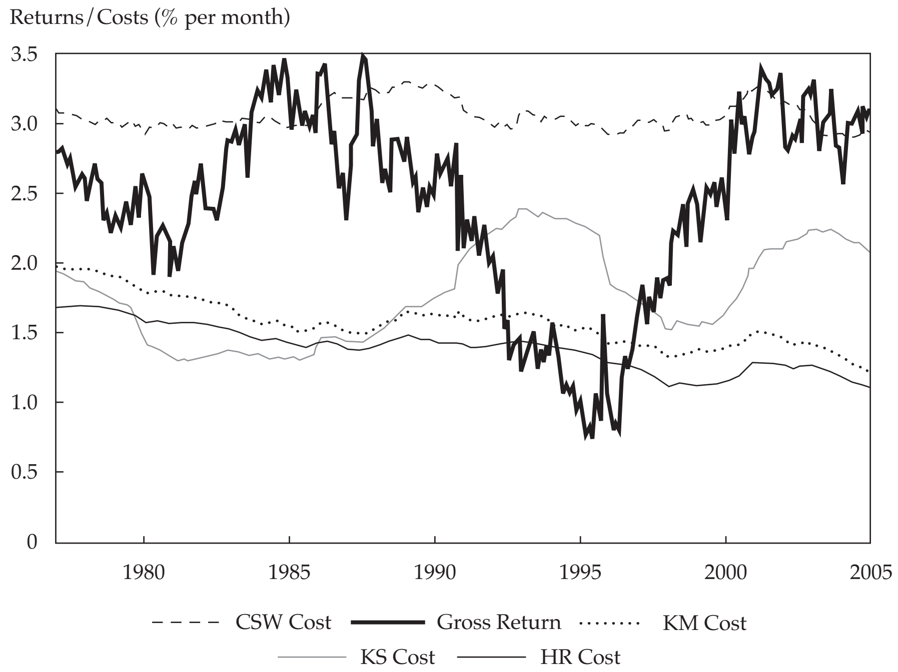
of the sample period. After adjusting for HR (KM) transaction costs, the net returns for the most illiquid stocks are 1.20 percent (1.01 percent) for 1972–1988 and 0.94 percent (0.76 percent) for 1989–2005. After adjusting for KS estimates of trading costs, the net returns are 1.15 percent for the first half of the sample and 0.19 percent for the second half of the sample. Finally, after adjusting for CSW estimates of trading costs, the net returns are –0.37 percent for the first half of the sample and –0.91 percent for the second half.

The overall conclusion is that although the potential returns from the long–short strategy have declined over time, market impact costs have declined even more. Thus, the potential profits from the long–short strategy are higher for the second half of the sample when trading costs are measured as in KS or CSW.

Figure 1 depicts the five-year moving averages of the gross returns from the long–short strategy for the most illiquid stocks, as well as the transaction costs obtained by using the analysis of HR, KM, KS, and CSW for a $1 million long–short position. As measured by gross returns, the potential profits are quite variable: They were high in the early 1980s and early 1990s and from 2000 to 2005.

The transaction-cost estimates obtained on the basis of CSW are consistently higher than those obtained by using KS, even though both methods capture market impact costs. The reason for this difference may be the nonlinear cost function estimated for CSW. Some readers have suggested that the potential profits from the earnings drift should decline with transaction costs. Indeed, that is the case with the overall earnings momentum strategy. For the most illiquid stocks, however, our results suggest that although transaction costs have declined over time, the profits from a PEAD strategy have not. This apparent anomaly can be explained if we find the transaction costs to be higher than the potential earnings momentum profits. In other words, if the transaction costs are not binding, then the potential profits from the drift do not necessarily have to decline over time with the trading costs. In fact, we found that the transaction costs (including commissions and short-sale costs) for a sufficiently large long–short position are larger than the potential profits from the drift.

Figure 1. Returns and Costs of SUE- and Illiquidity-Sorted Portfolios, 1977–2005



Notes: This figure shows the five-year rolling averages of returns and transaction-cost estimates for a hedge portfolio consisting of only the most illiquid decile of stocks. The hedge portfolio is long the highest-SUE decile and short the lowest-SUE decile and includes only stocks in the most illiquid portfolio.

Short-Sale Costs. The costs of short selling are important for the earnings momentum strategy because of the requirement of going short the low-SUE portfolio. We turned to Cohen, Diether, and Malloy (2007), who used a proprietary database of stock-lending activity from a large institution that is a market maker in many small stock-lending markets. The sample period for this database is September 1999–August 2003. Table 1 of their article provides an estimate of annual short-selling costs of 3.94 percent for stocks at the 15th percentile of NYSE market capitalization. This estimate amounts to about 33 bps per month. Note that this estimate may be an understatement for the earlier part of our sample, when short-selling costs may have been higher.

Consider the net returns from Table 5. After adjusting for transaction costs by using HR, KM, KS, and CSW estimates, the net returns are 1.07 percent, 0.88 percent, 0.66 percent, and –0.65 percent per month, respectively. After subtracting the short-selling costs of 33 bps per month, the gross returns of 2.43 percent are further reduced to 0.74 percent, 0.55 percent, 0.33 percent, and –0.98 percent. Thus, transaction costs, including short-sale costs, account for anywhere from 70 percent (= 1 – 0.74/2.43) to 100 percent of the gross returns, depending on how the transaction costs are measured.[13]

Summary of Transaction Costs. We analyzed trading costs from a number of different perspectives, including proportional effective bid–ask spreads, dynamic institutional trading costs, and market impact costs. Consider the most illiquid stocks. The effective bid–ask spreads for the round-trip buy and sell trades amount to 1.07 percent per month over the three-month holding period. The dynamic cost analysis of institutional trading costs using KM data suggests that transaction costs (including commissions but excluding market impact costs) are 1.55 percent. The market impact costs (excluding commissions) according to the KS methodology amount to 1.77 percent for a long–short position of $1 million. Finally, the market impact costs according to the CSW estimates (excluding commissions) amount to 3.08 percent. The market impact costs are instrumental in eliminating the potential profits from a long–short strategy that exploits the post-earnings-announcement drift. In addition to all these trading costs, the short-selling costs amount to 33 bps per month.

Overall, most of the paper profits disappear after accounting for trading costs. The transaction costs account for 70–100 percent of the potential profits from the earnings momentum strategy. The main reason is that the largest potential profits are obtained for the highly illiquid stocks that have high trading costs.

Conclusion

The PEAD, one of the most robust anomalies, was first documented by Ball and Brown (1968). A portfolio that is long high-earnings-surprise stocks and short low-earnings-surprise stocks earns a monthly return of 1.31 percent. A long-standing, robust anomaly that can be exploited by using a simple long–short strategy points to a violation of semistrong-form efficiency. What is especially intriguing is that stock prices do not respond completely and immediately to information as visible and freely available as earnings announcements. Moreover, the earnings momentum anomaly has persisted for almost four decades.

We showed that transaction costs inhibit the exploitation of the PEAD and thus caused it to seem robust for more than three decades. Earnings momentum profits accrue mainly in the highly illiquid stocks, which have high trading costs and high market impact costs. Transaction costs account for 70–100 percent of the potential paper profits from a long–short strategy designed to exploit the earnings drift. A $5 million long–short position designed to exploit the PEAD is not profitable because of the market impact costs of a long–short strategy. This lack of profitability suggests that the violations of the efficient market hypothesis arising from earnings momentum are not so egregious after all. Moreover, the lack of profitability is consistent with the notion of efficiency in Jensen (1978) and Rubinstein (2001).

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This article qualifies for 1 CE credit.

Appendix A. Cost Estimates

Keim and Madhavan. Keim and Madhavan (1997) estimated the trading costs for 21 institutions from January 1991 through March 1993. These costs include commissions paid, as well as price impacts of trades. We used the regression results of Keim and Madhavan (see their Table 5) to estimate trading costs for each stock transaction. To be conservative, we assumed that our investor is a value (long-term) trader. Keim and Madhavan showed that trading costs are higher for technical and index traders, possibly because of the higher demand for immediacy in the execution of such traders' orders. We set both the trade size and their NASDAQ dummy to zero (because our sample consists of NYSE and Amex stocks only). Our estimates of buy and sell trading costs are given by

$$C_i^{Buy} = 0.767 - 0.085\log(Mcap_i) + \frac{13.807}{P_i} \qquad \text{(A1)}$$

and

$$C_i^{Sell} = 0.505 - 0.059\log(Mcap_i) + \frac{6.537}{P_i}, \qquad \text{(A2)}$$

where C_i^{Buy} is the buyer-initiated cost, C_i^{Sell} is the seller-initiated cost, $Mcap_i$ is the market capitalization (in thousands of dollars), and P_i is the price for stock i. The costs in Equations A1 and A2 are percentages.

Hanna and Ready. Using transaction data for 1983–2001, Hanna and Ready (2005) estimated effective bid–ask spreads for NYSE and Amex stocks. Using market capitalization, share price, monthly turnover, and monthly volatility as independent variables, they fit a regression model for the spreads each year. Because we computed effective spreads by using transaction data for 1988–2005, we used our direct measures of the spreads over this period. For NYSE stocks over the 1983–87 period and for Amex stocks, we used the coefficient estimates from Hanna and Ready. For the pre-1983 period, we used the coefficient estimates for 1983. In this manner, we obtained measures for effective spreads for all the stocks in our sample (1972–2005).

Korajczyk and Sadka. Korajczyk and Sadka (2004) modeled the price-impact function as

$$\Delta p_{it} = \alpha_i + \lambda_i q_{it} + \Psi_i \Delta d_{it} + \varepsilon_{it}, \qquad \text{(A3)}$$

where Δp_{it} is the price change of stock i from trade $t-1$ to trade t as a consequence of a (signed) trade of q_{it} shares and d_{it} indicates the sign of the trade.

Fixed and variable costs of trading are measured by the coefficients ψ and λ, respectively. These market impact costs are estimated by using intraday transaction data and are calculated for each month for each stock for January 1993–May 1997. The costs are then estimated for the entire sample period by using cross-sectional relationships between the market impact costs and company characteristics.

The costs incurred in transactions each month are then calculated on the basis of the following equation:

$$\bar{x}_t + \frac{1}{2}\sum_i \frac{\lambda_{it}}{P_{it}^2}\left(w_{it}\bar{x}_t - a_{it}\right)^2 + \sum_i \Psi_{it}\left|w_{it}\bar{x}_t - a_{it}\right| = x_t, \qquad \text{(A4)}$$

where w_{it} is the weight, P_{it} is the price, $a_{it} \equiv w_{it-1}x_{t-1}(1 + r_{it})$ is the dollar value (via investments made at time $t - 1$) of the total portfolio of stock i at time t, and r_{it} is the stock return. In Equation A4, x_t measures the value of the portfolio before any transactions are made and $\bar{x}_t$ measures the value of the portfolio after transactions are made at time t. See Appendix A and Figure 2 in Korajczyk and Sadka (2004) for further details.

Chen, Stanzl, and Watanabe. Chen, Stanzl, and Watanabe (2004) modeled the price-impact function as

$$PI_{id} = a_i + b_i \frac{V_{id}^{\lambda_i} - 1}{\lambda_i} + \varepsilon_{id}, \qquad \text{(A5)}$$

where PI_{id} is the price impact and V_{id} is the dollar volume of stock i on day d. They estimated Equation A5 separately for buys and sells but only for separate size deciles. The estimates of Equation A5 are provided in Table 4 of their paper. Our choice of portfolio dollar value and the weights generated by the earnings drift strategy give us the dollar volume of trading in each stock for each month, which is then used in a straightforward way to calculate total transaction costs.

Notes

1. The other anomaly is price momentum, documented by Jegadeesh and Titman (1993).
2. See, for instance, Foster, Olsen, and Shevlin (1984) and Bernard and Thomas (1989, 1990).
3. Although the profits from a PEAD strategy that uses all the stocks have indeed declined over time, the PEAD strategy profits from illiquid stocks have not declined, as we show later in this article.
4. The concept of market efficiency with respect to an information set was defined by Jensen (1978) as the inability to profit from that information. Rubinstein (2001) defined it as minimally rational markets.
5. In the context of long-term contrarian investment strategies, Ball, Kothari, and Shanken (1995) showed that microstructure issues can create severe biases among low-priced stocks. We obtained qualitatively similar results when stocks priced below \$1.00 were eliminated from the sample; both the gross profits and the transaction costs are higher for low-priced stocks.
6. Sadka (2006) introduced a different liquidity risk factor that was identified by using intraday data. Sadka concluded that about half the abnormal returns of both momentum and PEAD strategies can be attributed to liquidity risk. Because the Sadka factor is nontraded, we did not use it in the calculation of abnormal returns. Nevertheless, adding this liquidity risk factor further reduces the abnormal returns of the PEAD strategy and makes profiting from such strategies more difficult.
7. In addition, we checked our results for robustness when sorting portfolios sequentially to ensure that all the portfolios were well populated. Moreover, we formed quintile portfolios instead of decile portfolios. The results from the quintile portfolios show that although the transaction costs are lower, the PEAD strategy profits are also lower, resulting in net profits that are lower than those reported elsewhere in this article.
8. Although doing so entails the use of future data in calculating the factor loadings, Fama and French (1992) showed that this looking forward does not affect the results.
9. We also used an interaction term of stock price and SUE (see Bhushan 1994). This coefficient is negative but statistically insignificant.
10. Brav and Heaton (2006) also found results inconsistent with Mendenhall (2004). They pointed out that Mendenhall's control for size-related differences in average returns is incomplete.
11. The transaction-based measures are computed at the transaction level and then averaged to obtain daily measures for each stock. See Chordia, Roll, and Subrahmanyam (2001) for details about these data.
12. In 1972, \$1 million was equivalent to about \$4.7 million in 2005 dollars.
13. In the real world, some investors may not take short positions. For these investors, the net returns are positive but net *alpha*, which accounts for market risk, is still negative. For instance, the high-SUE portfolio of the most illiquid stocks has gross returns (market alpha) of 2.39 percent (1.03 percent) (Table 2). The cost estimates from KS (CSW) are 0.98 percent (1.64 percent) (Table 5). Therefore, the net return to a long-only portfolio is still positive (after accounting for transaction costs) but the net alpha is either close to zero (KS) or negative (CSW).

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