Implications of Transaction Costs for the Post-Earnings-Announcement Drift

Jeffrey Ng
The Wharton School
University of Pennsylvania
1303 Steinberg Hall-Dietrich Hall
3620 Locust Walk
Philadelphia, PA 19104
teeyong@wharton.upenn.edu

Tjomme O. Rusticus
Kellogg School of Management
Northwestern University
2001 Sheridan Road, room 6216
Evanston, IL 60208
t-rusticus@northwestern.edu

Rodrigo S. Verdi
Sloan School of Management
Massachusetts Institute of Technology
50 Memorial Drive E52-403A
Cambridge, MA 02142
rverdi@mit.edu

First Draft: November 2005
Current Draft: October 2007

We thank David Aboody, Phil Berger (editor), John Core, Wayne Guay, Bob Holthausen, Mo Khan, S.P. Kothari, Shyam Sunder, Ro Verrecchia, Ross Watts, Joe Weber, an anonymous referee, and seminar participants at the University of Pennsylvania and Singapore Management University for their helpful comments. We appreciate financial support from the Accounting Research Center at the Kellogg School of Management (Northwestern University), the Sloan School of Management (Massachusetts Institute of Technology), and the Wharton School (University of Pennsylvania). We are also grateful for financial support from the Deloitte & Touche Foundation.

Implications of Transaction Costs for the Post-Earnings-Announcement Drift

ABSTRACT

This paper examines the effect of transaction costs on the post-earnings-announcement drift (PEAD). Using standard market microstructure features we show that transaction costs constrain the informed trades that are necessary to incorporate earnings information into price. This leads to weaker return responses at the time of the earnings announcement and higher subsequent returns drift for firms with high transaction costs. Consistent with this prediction, we find that earnings response coefficients are lower for firms with higher transaction costs. Using portfolio analyses, we find that the profits of implementing the PEAD trading strategy are significantly reduced by transaction costs. In addition, we show, using a combination of portfolio and regression analyses, that firms with higher transaction costs are the ones that provide the higher abnormal returns for the PEAD strategy. Our results indicate that transaction costs can provide an explanation not only for the persistence but also for the *existence* of PEAD.

1. *Introduction*

Post-earnings-announcement drift (PEAD) is the empirical finding that risk-adjusted returns drift in the direction of the earnings surprises in the months following earnings announcements (Ball and Brown [1968], Foster, Olsen, Shevlin [1984], Bernard and Thomas [1989, 1990]). Though it is possible that profitable trading opportunities could be uncovered from time to time, arbitrage theory suggests that informed investors acquainted with the PEAD literature should have arbitraged away the PEAD. Despite some evidence that transaction costs limit arbitrage in the PEAD setting (e.g., Bernard and Thomas [1989, 1990], Bhushan [1994]), transaction costs have not been used to provide an explanation for the *existence* of the PEAD.

A key innovation in our paper is that we rely on standard features in the market microstructure literature to analyze how transaction costs can offer a rationale for PEAD (section 2 describes our analyses in more detail). Prior studies that have examined the implications of transaction costs for PEAD generally argue that there is mispricing due to misvaluation by less informed investors and that informed investors are unable to fully correct the mispricing because of transaction costs (e.g., Bhushan [1994], Chordia et al. [2007]). Unlike these studies, we do not assume mispricing and do not treat transaction costs as a 'black box' that limits arbitrage. Instead we rely on the market microstructure literature to examine the impact of transaction costs on the process of price discovery (Lee [2001]). We show how transaction costs constrain profitable trades by informed investors that are required to drive the convergence of market price to fundamental value at the time of the earnings announcement. This leads to the initial underreaction to earnings news. When post-announcement private or public value-relevant news makes it profitable for informed traders to resume trading, their trades then move the market price towards the fundamental value, i.e., this is observed as the post-earnings–announcement-drift.

In our empirical analyses, we follow prior literature (e.g., Lesmond, Schill, and Zhou [2004], Korajczyk and Sadka [2004], Hanna and Ready [2005]) and use relative bid-ask spreads plus commissions as direct estimates of the transaction costs of making round-trip marginal trades. We also use an alternative measure of transaction costs developed by Lesmond, Ogden, and Trzcinka [1999]. This measure offers a possibly more comprehensive estimate of transaction costs that includes price impact and opportunity costs (e.g., immediacy costs), and has also been used in Lesmond et al. [2004] to examine the profitability of momentum-based trading strategies.

Our first prediction is that the market reaction to earnings surprises is smaller for firms whose shares have higher transaction costs. Thus, we examine the initial market response to earnings surprises for firms with different transaction costs. We find that firms whose shares have higher transaction costs experience smaller reactions to their earnings surprises. This is consistent with our prediction that transaction costs discourage the informed trades that are necessary to incorporate earnings information into price.

Our second prediction is that the drift in returns is larger for firms whose shares have higher transaction costs. Consistent with this hypothesis we find that, while the average transaction costs of the shares of all firms are relatively low, the transaction costs of the shares of the firms in the extreme earnings surprises portfolios are high. Taking into account these transaction costs significantly reduces the profitability of the trades made in these portfolios. For instance, the PEAD strategy using extreme decile portfolios generates 12-month equal-weighted size-adjusted returns of 11.92% from 1988 to 2005. However, the estimated profits reduce to 3.36% after the deduction of our most conservative estimate of transaction costs, measured as the sum of relative effective spreads and commissions. In further portfolio analyses, we find that firms with higher costs are the ones that provide the higher abnormal returns for the PEAD strategy (measured before transactions costs). For instance, the PEAD strategy among firms in the top (bottom) quintile of transaction costs generates 12-month size-adjusted returns of 14.61% (3.07%). The increase in returns, however, is associated with an increase in costs, and, despite the much higher abnormal returns, the estimated profits (measured after transactions costs) are statistically insignificant and sometimes negative. For example, the PEAD strategy among firms in the top (bottom) quintile of costs earns a net profit of 1.02% (1.84%).

We also investigate the effect of transaction costs on PEAD after controlling for other determinants of PEAD. This is important because Mendenhall [2004], unlike Bhushan [1994], finds no evidence that stock price (as a proxy for transaction costs) affects the magnitude of the PEAD. We find a similar lack of significant association between stock price and the PEAD in our empirical analyses. However, when we use our more direct measures of transaction costs, we find clear evidence that firms with higher transaction costs have larger PEAD. We conjecture that the difference in results with regards to transaction costs is due to the fact that price is a crude proxy for transaction costs. Similar to Mendenhall, we also find that arbitrage risk limits arbitrage.

Finally, to assess the robustness of our transaction cost explanation, we study the effects of transaction costs on alternative settings where there is a drift in returns. First, we apply our approach to the drift following revenue surprises and a combination of revenue surprises and earnings surprises (Jegadeesh and Livnat [2006]). We find that transaction costs account for most of the abnormal returns of these strategies. Second, we investigate the effect of transaction costs in the recent PEAD literature that uses analyst forecasts as the earnings expectation benchmark (Livnat and Mendenhall [2006], Doyle, Lundholm, and Soliman [2006]). While transaction costs explain a significant proportion of the returns of this strategy, economically and statistically abnormal returns remain feasible. Given that this innovation has only recently appeared in the academic literature, a potential explanation is that insufficient informed trading has developed for prices to move fully to the transaction cost bounds. In fact, we provide some evidence that the abnormal returns of this strategy have decreased in more recent years and that the magnitude of the abnormal returns appears to have converged to the magnitude of the transaction costs.

Our results are consistent with a recent working paper by Chordia et al [2007]. Neither our paper nor Chordia et al. are the first to show that the magnitude of PEAD is increasing in the magnitude of proxies for transaction costs - Bernard and Thomas [1989] and Bhushan [1994] have provided some early evidence of this relation. The contribution of both papers lies in the fact that both our paper and Chordia et al. are able to measure transaction costs more explicitly and this allows us to quantify the profitability of the PEAD strategy. However, the unique contribution of our paper is to use a market microstructure framework to show how transaction costs constrain informed traders from fully reacting to earnings news and to explain how the resumption of trading after the earnings announcement by these traders could lead to predictable drifts in returns. In this sense, our study shows that transaction costs can provide an explanation not only for the persistence but also for the *existence* of PEAD.

The remainder of the paper is organized as follows. The next section describes the implications of transaction costs for the speed in which the market reflects the information in earnings announcements. Section 3 describes the sample selection and the data. Section 4 presents the research design and the results of our analyses. Section 5 presents results from analyses that use analysts' earnings forecasts to compute earnings surprises. Section 6 concludes.

2. Transaction costs and the existence of the PEAD

In this section, we explain how market processes related to transaction costs can result in an initial underreaction at the earnings announcement and in a predictable post-announcement drift in returns. The discussion is motivated by Diamond and Verrecchia [1987] who demonstrate theoretically how short-sale restrictions and costs constrain informed trades on the sell side when there is bad news. As a result of this constraint, market prices do not immediately converge to the true value when there is bad news (i.e., there is underreaction to bad news) and the speed of the price convergence is also a function of the constraints. We extend the economic intuition of Diamond and Verrecchia to analyze how transaction costs on both the buy and the sell sides lead to an underreaction to good news and bad news, respectively. In addition, we illustrate how transaction costs lead to subsequent market correction (i.e., to the PEAD).

In our analyses, we rely on three standard and descriptive features in the market microstructure literature. First, market makers are less informed than informed traders such that market makers do not value firms directly, say from firm disclosures, but infer firm value from observing order flow and imbalances (Kyle [1985], Glosten and Milgrom [1985], Kim and Verrecchia [1994]). Further, they adjust the bid-ask prices by observing the net order flow arising from trades.[1] Second, informed traders trade only if the marginal value of the accumulated information exceeds the marginal cost of trading (Garman and Ohlson [1980], Lesmond et. al [1999], Lo, Mamaysky, and Wang [2004]). Third, informed trades result in permanent price movements whereas uninformed trades, e.g., liquidity trades, just create noise in the trading process and do not have a permanent effect on price (e.g., Kyle [1985], Hasbrouck [1991]).[2] The lack of price impact of liquidity trades may be due to the fact that these trades tend to be small and/or that the buy and sell trades often cross.

Our analysis also relies on the idea that informed traders can trade on their ability to quickly process public disclosures into *tradable private information* (Glosten and Milgrom [1985], Kim and Verrecchia [1994]). For example, Glosten and Milgrom [1985, p. 77] state that they refer to "the informed traders as insiders, even though other interpretations are possible, for example, they may merely be individuals who are particularly skilful in processing public information." This argument is supported by empirical evidence of immediate sharp price and volume reactions to public earnings announcements (Lee [1992]), of increases in informed trading during earnings announcements (Lee, Mucklow, and Ready [1993], Krinsky and Lee [1996]), and of

[1] We note that the fact that researchers have been consistently able to empirically document a drift in returns suggests that market makers are not adjusting prices to fundamental values.

[2] In fact, trades by uninformed traders may be necessary to create sufficient noise in the order flow to camouflage trades by the informed traders and to compensate market makers for losses suffered while trading with informed investors (Kyle [1985]).

PEAD-related trades by transient institutional investors (Ke and Ramalingegowda [2005]).

2.1 UNDERREACTION TO EARNINGS NEWS

To illustrate how transactions costs can lead to an underreaction to earnings news, we assume that a firm makes an earnings announcement that reflects an increase in its fundamental value from a pre-announcement price of $100 per share to a post-announcement price of $105 per share. For simplicity, we further assume that the only transaction cost is a bid-ask spread of $2, i.e., the pre-announcement bid (ask) price is $99 ($101).[3] The market price is the midpoint of the bid-ask spread, i.e., $100.

After learning the positive earnings news, an arbitrageur will start buying the shares of the firm because it is profitable to do so at the current market price of $100. In response, the market maker will then start increasing the bid-ask prices until the market price reaches $103 (i.e., bid and ask prices are at $102 and $104, respectively).[4] At this point, the expected price increase of $2 to the fundamental value of $105 is equal to the transaction cost of $2 and any further trades will result in losses. Hence, transaction costs create an upper bound to the upward price response to good earnings news such that there is an underreaction to news. Further, the underreaction will be larger if the firm has higher transaction costs. For example, if we assume transaction costs of $4 (instead of

[3] If other transaction costs such as brokerage commissions or information acquisition costs are considered, our analyses imply that the underreaction and the post-announcement drift are likely to be more severe. In the extreme, total transaction costs may be so high that informed trades may not occur and market prices will not adjust at the time of the earnings announcement.

[4] For example, when observing net buy trades, the market maker increases the bid (ask) price to $101.01 ($103.01), then to $101.02 ($103.02), and so on and so forth, until the bid (ask) price is at $102 ($104).

$2), then our analyses imply that market price will only move to $101 (instead of $103) during the earnings announcement.[5]

The above analyses of how transactions costs can lead to an underreaction to earnings news is also important in addressing one of the questions in Bernard and Thomas [1990, p. 33] who argue that if trades occur around earnings announcements, then the prices should fully reflect the fundamental value. We argue that trades by informed investors can occur, but the information about fundamental value need not be fully impounded into price since transaction costs creates bounds to trades. Further, trades can also occur as long as uninformed traders continue to trade (e.g., for liquidity reasons).

Based on the above analyses, our first prediction is that the market reaction to earnings surprises will be smaller for firms whose shares have higher transaction costs.

2.2 POST-ANNOUNCEMENT PRICE CONVERGENCE

Next, we discuss how the initial underreaction leads to a future drift in returns. This point is important because, although Bernard and Thomas [1989, p.33] acknowledge that transaction costs might lead to the initial market underreaction, they raise the question of whether transaction costs can lead to the observed post-announcement drift as transaction costs should also hinder post-announcement trading. We now show that post-announcement private or public news available to the arbitrageur can lead to price convergence even in the presence of transaction costs. The key to the price convergence is that the arbitrageur resumes trading only when it is profitable for him or her to do so.

---

[5] Following a similar logic, one can show that in the case of bad earnings news, transaction costs create a lower bound that prevents prices from fully moving down to the new lower fundamental value.

We continue with the illustration from section 2.1. Assume that in the post-announcement period, the arbitrageur receives some news about the firm. For simplicity, we assume that the expected value of the news is equal to zero, i.e., there is a 50% chance that the news is good news of $2 per share and a 50% chance of bad news of $2 per share.[6] If the news is positive, then it increases the fundamental value by $2 to $107. In this case it becomes profitable to buy the stock because the expected price increase of $4 ($107-$103) is more than the round-trip transaction cost of $2. So the arbitrageur continues to buy until the market price reaches $105. In contrast, if the news is negative and reduces the fundamental value by $2 to $103, it is not profitable to trade the stock at the current market price of $103 and the price remains at $103. Hence, the market price is expected to increase to $104 (50% x $105 + 50% x $103) despite the fact that positive and negative news are random.

An extrapolation of the above illustration is that a series of such post-announcement random news makes the expected market price converge to the fundamental value at the earnings announcement of $105 in a process that we may empirically observe as a drift in returns. Further, if the news is larger in magnitude, e.g., good or bad news of $5 per share, there will be complete price convergence to $105 since the market price will move to $108 ($105 + $5 - $2) after good news or to $102 ($105 - $5 + $2) after bad news. This results in an expected price of $105. We note that the above analysis also provides a potential explanation for the concentration of abnormal returns

[6] The assumption of equal probabilities of good and bad news is without loss of generality. The analysis holds for any probability of good news greater than zero. In fact, if good news are positively autocorrelated (i.e., the probability of good news conditional on a prior good news is greater than 50%), then the price convergence to fundamental value will be faster.

around future earnings announcements because around such dates value-relevant news is more likely.

Based on the above analyses, our second prediction is that the drift in returns after earnings surprises will be larger for firms whose shares have higher transaction costs.[7]

3. Sample selection and variable measurement

We obtain quarterly earnings announcement dates and quarterly earnings from the Compustat quarterly files. We restrict the sample to earnings announcements from calendar years 1988 to 2005 due to the data requirements for our market microstructure variables, which we compute using data from the Institute for the Study of Security Markets (ISSM) and the NYSE Trades and Quotes (TAQ) databases.[8] We retain firm-quarters for firms with ordinary shares (CRSP share code of 10 or 11) listed on NYSE or AMEX (CRSP exchange code of 1 or 2) as of the earnings announcement date. Our sample size is 126,386 firm-quarter earnings announcements after restricting the announcements to those with sufficient data to compute the variables described below. The restriction to NYSE and AMEX firms is for consistency with most of the prior work on the PEAD (Bernard and Thomas [1989, 1990], Bhushan [1994], Bartov et al. [2000], among others). In untabulated analyses, we find that our results are robust to the inclusion of NASDAQ firms.

---

[7] Our analyses predict that the transaction costs may lead to underreaction in any setting in which there is a news event. As noted in Barberis, Shleifer, and Vishny [1998] and Hirshleifer [2001], underrreaction to news events is a common finding in the literature. For example, in addition to earnings news, there is evidence of underrreaction to stock repurchases (Ikenberry, Lakonishok, and Vermaelen [1995]), stock splits (Ikenberry, Rankine, and Stice [1996]), debt rating downgrades (Dichev and Piotroski [2001]), and analyst forecast revisions (Gleason and Lee [2003]), among others.

[8] The NYSE TAQ data is available from January 1993. The ISSM data is available from January 1983 to December 1992. These databases provide comprehensive microstructure data for the NYSE and AMEX firms in our sample. Bid and ask volumes, which are required for the cleaning of the data (see Appendix A), are missing from the ISSM data in 1987. Hence, we restrict our sample to January 1988 onwards.

3.1 MEASUREMENT OF EARNINGS SURPRISES

Many alternative measures of earnings surprises have been used in the PEAD literature to develop the PEAD strategies. The traditional measure is computed as the seasonal change in quarterly earnings scaled by either the standard deviation of prior unexpected earnings or prior market value of equity (Bernard and Thomas [1989, 1990], Livnat and Mendenhall [2006]). We use the measure scaled by market value as this measure provides us with the largest sample and yields larger hedge portfolio returns on the PEAD strategy.[9] We define earnings surprise for firm *i* in fiscal quarter *q*, $UE_{i,q}$, as:

$$UE_{i,q} = \frac{E_{i,q} - E_{i,q-4}}{MV_{i,q-4}} \tag{1}$$

where $E_{i,q}$ is the most recent quarterly earnings (Compustat #8), $E_{i,q-4}$ is the quarterly earnings four fiscal quarters before, and $MV_{i,q-4}$ (Compustat #14 x Compustat #61) is the market value at the end of the fiscal quarter four fiscal quarters before. After computing the earnings surprises, we assign firms into decile and quintile portfolios based on the distribution of the earnings surprises in the prior quarter. The use of the prior quarter's earnings surprises distribution avoids a look-ahead bias when determining the relative magnitude of earnings surprises (Foster, Olsen, and Shevlin [1984]).

3.2 MEASURES OF TRANSACTION COSTS

In this section, we describe the measures of transaction costs that we use to assess the profitability of the PEAD strategy. These measures are effective spreads, quoted spreads, commissions, and the limited dependent variable (*LDV)* measure developed by Lesmond et al. [1999]. These measures have been used in prior research to examine the

[9] Our main inferences remain when we use standard deviation of prior unexpected earnings as the scalar. With this alternative measure, we have a sample size of 96,944 earnings announcements, for which we find 12-month hedge portfolio returns of 6.70% that reduce to 2.84% after deducting effective spreads and commissions.

profitability of other trading strategies (e.g., Knez and Ready [1996], Lesmond et al. [2004], Korajczyk and Sadka [2004], Hanna and Ready [2005]). As noted in Keim and Madhavan [1998], Lesmond et al. [2004], and many others, measures of transaction costs are likely to be conservative in that they only capture the estimable components of transaction costs. For example, they ignore the price movements induced by large trades of large quantities.

The most commonly used and direct estimates of transaction costs are bid-ask spreads estimated using relative effective spreads or relative quoted spreads. Relative quoted spread measures potential transaction costs for non-executed marginal trades while relative effective spread measures the average transaction costs for executed marginal trades. One advantage of using spreads is that they are directly observable. Further, it is also difficult for arbitrageurs to avoid the payment of spreads by trading through the upstairs market because upstairs market makers screen for information-motivated orders, and because the upstairs market is less anonymous than the downstairs market (Keim and Madhavan [1996]). In fact, Smith, Turnbull, and White [2001] provide evidence that upstairs market makers effectively screen out information-motivated orders (and execute large liquidity-motivated orders at a lower cost than the downstairs market).

We use the intra-day trades and quotes from the ISSM and TAQ databases to calculate relative spreads. To ensure data integrity, we remove trades and quotes that are likely to be errors or outliers as discussed in Appendix 1.A for the ISSM database and Appendix 1.B for the TAQ database.

The relative effective spread is based on the notion that trade is only costly to the investor to the extent that the trade price deviates from the true price, approximated by the bid-ask midpoint. To compute each effective spread, we match each intraday trade to an intraday quote using the standard Lee and Ready [1991] algorithm described in Appendix 1.C. This process attempts to remove quotes for which trades have not been executed and could potentially reduce the noise from the transaction cost estimation. For each trade-matched quote at time *s* for firm *i*, we compute the intraday relative effective spread, $IntraESpread_{i,s}$, as:

$$IntraESpread_{i,s} = \frac{2\,|\,trade\ price_{i,s} - (bid\ price_{i,s} + ask\ price_{i,s})/2\,|}{trade\ price_{i,s}} \qquad (2)$$

where $ask\ price_{i,s}$ ($bid\ price_{i,s}$) is the ask price (bid price) for the quote at time *s* for firm *i*, and $trade\ price_{i,s}$ is the trade price at which the trade is executed at time *s* for firm *i*. We compute the daily relative effective spreads by size-weighting the intraday relative effective spreads.

The underlying assumptions of the quoted spread are that market makers set the prevailing quotes and stand on the other side of the customer trades, and that investors cannot trade within the quoted spread. For each quote at time *s* for firm-quarter *i*, we compute the intraday relative quoted spread, $IntraQSpread_{i,s}$, as:

$$IntraQSpread_{i,s} = \frac{ask\ price_{i,s} - bid\ price_{i,s}}{(ask\ price_{i,s} + bid\ price_{i,s})/2} \qquad (3)$$

where $ask\ price_{i,s}$ ($bid\ price_{i,s}$) is the ask price (bid price) at time *s*. We compute daily relative quoted spreads by equal-weighting the intraday relative quoted spreads.

Consistent with the prior literature (e.g., Bhardwaj and Brooks [1992], Lesmond et al. [2004]), we add average daily brokerage commission rates to the average daily relative effective (quoted) spreads. We use the standard commissions schedule from CIGNA Financial Services that is found in Lesmond et al. [2004]:

Trade size (V)	Commission
$0-$2,500	$29 + 0.017V
$2,500.01-$6250	$55 + 0.0066V
$6250.01-$20,000	$75 + 0.0075V
$20,000.01-$50,000	$99 + 0.0022V
$50,000.01-$500,000	$154 + 0.0011V
$500,000+	$254 + 0.0009V

For stocks under $1.00 per share, the commission is $38 plus 4% of trade size. The overriding minimum commission is $38 per trade.

To compute the daily percent commission rate, we first obtain the average trade size by averaging the dollar volume of the trades within the day. We then use the average trade size and the above schedule to estimate the commission for an average trade. Finally, we estimate daily percent commission rate by dividing the commission by the average trade size. We then equal-weight the aggregate daily relative effective (quoted) spread plus percent commission rate in the earnings announcement month to estimate the average transaction cost, *ESpread* (*QSpread*). Brokerage commissions declined substantially in the later part of our sample period. To make sure that our analyses are not dependent on potentially overstated commission schedules, we only include the commission at the initiation of the arbitrage position and not at the liquidation of the position. The effect is to cut the commission in half.[10]

Though bid-ask spreads are direct estimates of transaction costs, the literature emphasizes that spreads understate the true transaction costs for the arbitrageur by omitting relevant transaction costs such as price impact and opportunity costs. Lesmond

[10] As a further robustness check, we have redone our analyses using spreads only and the results are available upon request. These (untabulated) analyses indicate that while the magnitude of the transaction costs is reduced, our findings are qualitatively similar. In particular, transaction costs significantly reduce the profitability and explain the cross-sectional variation in the abnormal returns of the PEAD trading strategy.

et al. [1999] provide an alternative and possibly more comprehensive estimate of transaction costs by using the transaction cost implied by investors' trading behavior. As this measure is based on limited dependent variable modeling, Lesmond et al. term this measure *LDV*. Ideally, the measure captures all the costs that traders take into account when making their trading decisions. A maintained assumption in the model that estimates *LDV* is that arbitrageurs trade only if the marginal value of the accumulated information exceeds the marginal cost of trading. Given that any delayed stock price reaction is attributed to transaction costs, it would be tautological to estimate it using returns after the earnings announcements. Instead, following Lesmond et al., we calibrate the model using the market model with one year of daily returns that end before the earnings announcement month. In this setting, the maintained assumption that all frictions are due to transaction costs is most appealing. However, to the extent that we still pick up other frictions, the *LDV* measure may be overstated. A further discussion of the calculation and limitations of the *LDV* measure is provided in Appendix 1.D. This measure has also been used in Lesmond et al. [2004] to evaluate the profitability of the momentum trading strategy.

3.3 OTHER VARIABLES

For each firm-quarter, we also compute measures of asset pricing risk (firm beta, size, and book-to-market), investor sophistication (*Institution*), and arbitrage risk (*Volatility*). This is important in order to address alternative explanations for the post-earnings-announcement-drift (Ball [1992], Bartov et al. [2000], Mendenhall [2004]). *Beta* is estimated from a market model regression for each firm with at least 18 monthly returns over the past 60 months ending in the month before the announcement month.

Size is the market value of equity at the end of the previous fiscal quarter. *BEME* is the ratio between the book value of equity and the market value of equity at the end of the previous fiscal quarter. *Institution* is the percentage ownership held by the institutional investors of the firm at the end of the calendar quarter before the earnings announcement. This data is collected from Thomson Financial. *Volatility* is the standard deviation of the residuals of a regression of daily returns on the S&P500 during the twelve months ending in the announcement month, with the requirement that at least 24 daily returns are available for the regression.[11] *Price* is the average daily closing price of the firm in the announcement month. *Volume* is the average daily dollar trading volume of the firm during the earnings announcement month. Daily dollar trading volume is the product of the daily closing price and the daily number of shares traded, both of which are obtained from CRSP. Finally, market depth is computed as (the number of shares the market maker offers to buy x the ask price) + (the number of shares the dealer is willing to sell x the bid price). Intraday depth is then averaged during the day and daily depth is averaged during the earnings announcement month, in order to estimate the average depth, *Depth*.

4. Results

4.1 DESCRIPTIVE STATISTICS

Table 1 – panel A presents firm characteristics for each *UE* decile. Firms in the extreme deciles have higher beta and lower market values and book-to-market ratios than firms in the middle deciles. In addition, firms in the extreme deciles also have higher

[11] Mendenhall [2004] defines volatility based on monthly returns over the past 48 months. We use daily returns to get a more timely and precise measure of volatility. Indeed, while the volatility results hold for both measures, the ability of volatility to explain the magnitude of the PEAD is stronger when using the daily volatility measure.

return volatility, lower institutional ownership, and lower share price. With the exception of book-to-market, these characteristics are relatively similar for firms in the top and bottom deciles. Hence, the differential returns are unlikely to be due to differences in expected returns. In fact, one could argue that the similarity in the risk characteristics for firms with extreme earnings surprises suggests that a hedge portfolio will result in a trading strategy with little risk exposure. This argument, however, does not hold from the transaction costs perspective because investors have to incur high costs on both the buy and the sell sides of the strategy (i.e., transaction costs cannot be 'hedged' away).

Panel B presents the return and transaction cost characteristics for each *UE* decile. Though we provide evidence of abnormal returns using alternative asset pricing models later in the paper, we follow the tradition in the PEAD literature by using size-adjusted returns as the measure of abnormal returns for most of our analyses. To calculate 3-month (12-month) abnormal returns, *AbRet3* (*AbRet12*), we collect monthly returns from CRSP for the 3-month (12-month) period beginning from the month following the announcement month. We intentionally allow for some time between the earnings announcement and the portfolio formation date to allow for the possibility that informed investors trade during earnings announcements and move prices to the transaction cost bound.

We compute the size-adjusted return for each firm by subtracting the buy-and-hold return in the same CRSP size-matched decile from the buy-and-hold return of each firm, with size measured as the market capitalization at the beginning of the calendar year. When a security delists during the return cumulation period, we include the delisting return in the month of the delisting if the delisting return is available. For the delisted firms, we reinvest the remaining proceeds in the CRSP size-matched decile until the end of the return cumulation period. If the delisting return is not available, we assume a delisting return of -100%. We then determine the average buy-and-hold return for each *UE* decile by averaging the buy-and-hold returns of all firms in the portfolio.

Consistent with the PEAD literature, we find that equal-weighted abnormal returns increase from *UE* decile 1 to *UE* decile 10. Firms in the top (bottom) decile generate 3-month abnormal returns of 3.23% (-2.16%) and 12-month abnormal returns of 7.33% (-4.59%), confirming previous findings that post-announcement returns are positive (negative) for firms releasing positive (negative) earnings surprises. Firms in the extreme *UE* deciles, however, also have higher transaction costs. For instance, the average *ESpread* (*LDV*) for firms in the bottom decile is 4.53% (5.69%) and 4.04% (6.05%) for firms in the top decile, as compared to *ESpread* (*LDV*) of 1.48% (1.93%) for firms in decile 5. We note that our average spreads and the *LDV* are similar to those reported by Lesmond et al. [2004, p.363].

Panel C provides further evidence of the difficulties of implementing trades, especially large trades, in firms in the extreme deciles. Trades in these firms tend to create more price impact as measured by *Depth* and *Volume*. For example, a depth of $49,410 for the bottom decile suggests that on average, a buy (sell) trade of $24,705 ($49,410 / 2) will lead to upward (downward) price impact. Consistent with high transaction costs and high price impact for the extreme deciles, the average trade size for the extreme deciles tends to be small. In addition, a larger proportion of firms in the extreme deciles have few daily trades. For example, 21% (26%) of the firms within the top (bottom) decile have an average of five or fewer daily trades in the announcement month, compared to 9% for decile 5.

Panel D provides further details of the transaction cost characteristics for each *UE* decile. Specifically, we measure the first quartile, median, and third quartile of daily spreads in the announcement months in our sample. This result is important because it shows that even if one assumes that the arbitrageur is good at market timing and executes transactions at the bottom quartile of the distribution of trading costs within the extreme *UE* deciles, the profitability of the PEAD strategy will still be significantly reduced by transaction costs. We note though that this assumption is unlikely to be descriptive because large trades are more likely to be executed outside the quoted spreads (Bessembinder [2003]).

4.2 INITIAL MARKET RESPONSE TO EARNINGS ANNOUNCEMENTS

In section 2.1, we predict that the magnitude of the market response to earnings surprises is smaller when transaction costs are higher because transaction costs inhibit informed trades that are required for price adjustment. We test this hypothesis using earnings response coefficient (ERC) regressions that examine the effect of the transaction costs on the market response to earnings surprises. Our general regression specification is as follows:

$$Market\ response = \beta_0 + \beta_1\ Surprise + \beta_2\ Surprise\ x\ Cost + \beta_3\ Surprise\ x\ Beta + B_4\ Surprise\ x\ Size + \beta_5\ Surprise\ x\ BEME + \sum \beta_k\ Control\ Variable_k + \varepsilon \qquad (4)$$

where *Market Response* is either *AbRet3d* or *AbRet4q* described below, *Cost* is either *ESpread*, *QSpread*, or *LDV*, and all the other independent variables are as defined earlier. We control for *Beta*, *Size*, and *BEME* because of prior evidence that risk and growth opportunities are cross-sectional determinants of the market response to earnings surprises, and we include the main effect for these variables as *Control Variable*$_k$ (e.g., Collins and Kothari [1989], Easton and Zmijewski [1989]). To reduce the effect of outliers and to facilitate the interpretation of the coefficients on the interaction terms, we rank *Cost*, *Beta*, *Size*, and *BEME* into quintiles within each calendar quarter and re-scale the ranks to range from zero to one.

In our baseline regression we use the size-adjusted returns in the three days around the earnings announcement (*AbRet3d*) as our measure of the *Market Response*. The earnings surprise is computed using the seasonal random walk model (*UE*). It is well known that the earnings four quarters before the earnings announcement are a noisy proxy of the market's expectation of earnings. This results in a classical errors-in-variables problem that manifests itself in low earnings response coefficients. This causes problems in our inferences if the noise in the earnings expectation model is related to our transaction costs variables. For example, it is likely that firms with high transaction costs have a poorer information environment, which implies that a higher fraction of the total earnings news is revealed at the earnings announcement date. This in turn may result in a higher market response at the earnings announcement, opposite to our prediction that transaction costs lower the market response.

We try to address this concern in two ways. First, we extend the return window backwards (Kothari and Sloan [1992]). We start cumulating the size-adjusted returns from the second day after the earnings announcement four fiscal quarters ago (i.e., after the release of the lagged earnings used to construct earnings surprise) until the first day after the earnings announcement for the current fiscal quarter. We label this measure of return *AbRet4q*. By lengthening the return window, we capture more of the earnings related news that is discovered before the earnings announcement. This reduces the error-in-variables problem and should result in higher ERCs and fewer opportunities for bias related to the noise. Our second approach is to use the latest analyst consensus forecasts from I/B/E/S to proxy for the market's expectation of earnings and to compute earnings surprise as the actual earnings per share minus the median analyst consensus forecast, scaled by the share price at the end of the fiscal quarter (*Analyst UE*) (Brown et al. [1987]).

The regression results are presented in Table 2. The first three columns present the results with the three-day abnormal return as the dependent variable (*AbRet3d*) and a seasonal random walk model for unexpected earnings (*UE*). Consistent with our argument above, the coefficient on the earnings surprise main effect is very small, indicating severe measurement error problems. When we turn to the interaction terms, only the results using *LDV* are consistent with our hypothesis that the earnings response coefficients are smaller for firms with higher transaction costs. However, as discussed above, these weak results could be a function of measurement error in the unexpected earnings. Thus, in the next three columns we replace the dependent variable by the yearly measure of contemporaneous stock returns (*AbRet4q*). In this case, the effects are strong and highly significant for effective and quoted spreads but are statistically indistinguishable from zero for *LDV*. Finally, in the last three columns, we replace the measure of unexpected earnings by a measure that uses analysts' expectations of earnings (*Analyst UE*). In this case, we again find strong evidence of the negative relation between the earnings response coefficient and transaction costs. With the exception of column VI, each of the last six columns suggests that the ERC is reduced by more than half when we move from the quintile with the lowest transaction cost to that with the highest transaction cost.[12] For example, in column IV, the ERC is 6.96 for the quintile with lowest *ESpread*, and drops by 4.02, or 58%, when we move to the quintile with the highest *ESpread*.

Overall, the results in Table 2 are consistent with our hypothesis that firms with higher transaction costs have lower earnings response coefficients because transaction costs prevent informed trades required for the price adjustment to earnings news.

4.3 PROFITABILITY ANALYSIS

Table 3 presents our profitability analyses for the PEAD strategy. Panel A (B) presents the analyses using equal-weighting (value-weighting). We compute profits by deducting the transaction costs from the abnormal returns. In particular, for firms in the bottom decile of unexpected earnings, we first multiply the returns by negative one (since the strategy takes a short position on firms in the bottom decile) and then deduct the transaction costs. For firms in the top decile, we subtract the transaction costs from the returns. *EProfit*, *QProfit*, and *LDVProfit* are the profits after deducting effective spreads, quoted spreads, and *LDV*, respectively.

In panel A, we show that firms in the top (bottom) *UE* decile generate 3-month abnormal returns of 3.23% (-2.16%) and 12-month returns of 7.33% (-4.59%). This implies that the PEAD strategy generates 3-month hedge portfolio returns of 5.38% and 12-month hedge portfolio returns of 11.92%. The strategy, however, earns 3-month (12-

[12] In untabulated robustness analysis we control for potential non-linearities in the earnings-returns relation by including an interaction term between earnings surprise and the absolute value of the earnings surprise. The coefficient on this interaction term is negative and significant. However, our transaction cost results remain economically and statistically significant.

month) profits of -3.18%, -6.88%, and -6.35% (3.36%, -0.34%, and 0.19%) after deducting *ESpread*, *QSpread*, and *LDV*, respectively. The smaller profitability for the 3-month holding period, compared to the 12-month holding period, is mainly due to the higher transaction costs of more frequent rebalancing with shorter holding periods.

In panel B, we note that the abnormal returns to a value-weighted strategy are equal to 0.09% (2.35%) in the next three months (twelve months) subsequent to the earnings announcement. The substantial reduction in drift when switching from equal-weighted to value-weighted abnormal returns is expected given that transaction costs are proportionally higher for smaller firms, and is consistent with the finding in prior literature that the PEAD is larger for small firms (Bernard and Thomas [1989, 1990]).[13]

Overall, the results in Table 3 indicate that the profitability of the PEAD strategy is significantly reduced after taking into account transaction costs. Another important implication of our above analyses is that in the presence of transaction costs, short holding periods for a trading strategy may result in significant losses.

4.4 THE EFFECT OF TRANSACTION COSTS ON THE MAGNITUDE OF THE DRIFT

In section 2.2, we predict that the returns drift will be larger for firms whose shares have higher transaction costs. To test this hypothesis, we repeat the portfolio analysis after sorting the firms independently into quintiles based on earnings surprises

[13] Prior research regularly excludes so-called "penny stocks" because these stocks are expected to have high transaction costs. Since transaction costs are the focus of our analysis, we do not exclude them in our main analyses. In untabulated analysis, we restrict our sample to firms whose stock prices at the fiscal quarter end are above $5. This reduces the sample to 110,071 observations, but the inferences are unchanged. For instance, we find 12-month hedge portfolio returns of 7.06%, which reduce to profits of 3.04% after deducting effective spreads and commissions.

and transaction costs. We choose quintiles rather than deciles to ensure that each of the 25 portfolios is populated.

Table 4 – panel A presents the abnormal returns and effective spreads for the 25 *UE-ESpread* portfolios and for the strategy that buys (sells) firms in the top (bottom) *UE* quintile for each *ESpread* quintile. We find that hedge portfolio returns are smaller than 5% for the bottom three quintiles of effective spread (i.e., the most liquid firms), and 8.68% and 14.61% for the top two quintiles of effective spreads. Panel A also presents the mean effective spreads. By construction, the mean spreads increase in the *ESpread* quintiles. Most importantly, we find that the profitability of trades within each *ESpread* quintile is generally economically insignificant. For example, the implementation of the strategy within the *ESpread* quintile 5 (1) generates abnormal returns of 14.61% (3.07%) but profits of only 1.02% (1.84%). Hence, despite the higher abnormal returns for firms with higher transaction costs, the profits are not higher and may even be lower when taking into account the higher transaction costs.

Panels B and C repeat the analyses with quoted spreads and the *LDV*. The results are largely consistent with the results in panel A. That is, although abnormal returns are higher in firms with higher transaction costs, the profitability of the strategy within each transaction costs quintile is generally insignificant, and may even be negative.

The results in Table 4 are based on size-adjusted returns, but it is important to assess the robustness of our findings to abnormal returns derived from alternative asset pricing models. Thus we repeat the portfolio analysis using portfolio time-series regressions of returns in excess of the risk-free rate on the commonly used Fama and French [1993] three-factor model. We also augment this model with the Pastor and

Stambaugh [2003] liquidity factor since Sadka and Sadka [2004] argue that it is liquidity risk, not liquidity-related transaction costs, that determines the magnitude of the PEAD. In addition, Sadka [2006] provides evidence that controlling for liquidity risk results in a significant reduction in the hedge portfolio returns from the PEAD strategy.

For each of the 25 portfolios sorted on unexpected earnings and a particular transaction cost measure, we obtain the monthly hedge portfolio returns (i.e., alphas) for the next twelve months and regress the portfolio excess returns on the corresponding monthly market factors. For comparability with our earlier analyses, we multiply the monthly alphas by 12 to estimate the abnormal returns for 12-month periods. To compute 12-month profits, we subtract our transaction cost estimates from the 12-month alphas.

Table 5 – panel A presents factor alphas and factor profits for *UE-ESpread* portfolios. The alphas increase from *ESpread* quintile 1 to *ESpread* quintile 5, consistent with the earlier evidence that larger abnormal returns are generated by firms with higher transaction costs. For example, the 12-month alpha derived from the Fama and French [1993] three-factor model is 2.78% (11.74%) for *ESpread* quintile 1 (quintile 5). When we examine the profitability of the trading strategy, we find that the profits are largely insignificant and possibly even negative. For example, the profit is 1.53% (-2.89%) for *ESpread* quintile 1 (quintile 5). We also find that controlling for liquidity risk by adding the Pastor and Stambaugh [2003] liquidity factor has a minimal impact on the hedge portfolio returns. In addition, there is still substantial variation in the returns across quintiles of transaction costs after controlling for liquidity risk. This result suggests that transaction cost is an important determinant of PEAD even after controlling for liquidity

risk as captured by the Pastor and Stambaugh [2003] factor. Panels B and C repeat the analyses for portfolios sorted on *QSpread* and *LDV*, and the results are similar.

Overall, the results in Tables 4 and 5 show that the PEAD is concentrated among firms with high transaction costs. Most importantly, we show that the high abnormal returns are substantially reduced after the transaction costs are taken into account.

4.5 DETERMINANTS OF THE MAGNITUDE OF THE PEAD

In this section, we investigate the effect of transaction costs on the PEAD after controlling for other documented determinants of the magnitude of the PEAD. This is important because transaction costs and arbitrage risk can both limit arbitrage activities (Pontiff [2006]).[14] In addition, unlike Bhushan [1994], Mendenhall [2004] finds no evidence that stock price, as a proxy for transaction costs such as bid-ask spreads and commissions, is associated with magnitude of the PEAD. We revisit this issue using our measures of transaction costs.

Following the literature, we run Fama-MacBeth [1973] regressions of firm-specific returns on the unexpected earnings and various determinants of the PEAD (Bhushan [1994], Bartov, Krinsky, and Radhakrishnan [2000], Mendenhall [2004]). We emphasize that these regressions cannot be used to determine the profitability of the PEAD strategy. The determination of profitability requires the deduction of transaction costs from abnormal returns, which is what we did in our earlier analyses. The results of the Fama-MacBeth regressions, however, are useful because they provide evidence on the incremental importance of the various determinants of the cross-sectional variation in

[14] As discussed in greater detail in Pontiff [2006], transaction costs (e.g., bid-ask spreads) are costs that are incurred when trades occur whereas holding costs (e.g., arbitrage risk) are costs that are incurred as long as a position remains open.

the PEAD. Stated differently, they help us identify the characteristics of the firms that experience more significant drifts in returns after earnings surprises.

We follow prior literature and replace the raw variables with their ranks in order to reduce the effects of measurement error. The *UE* variable is replaced by its quintile rank, recoded to range from 0 to 1 (Bernard and Thomas [1990], Bhushan [1994], Bartov et al. [2000]). Assuming linearity in the abnormal returns across the *UE* quintiles, the coefficient on this recoded *UE* quintile measures the hedge portfolio returns from buying (selling) firms in *UE* quintile 5 (*UE* quintile 1). Likewise, the measure of each determinant of the PEAD is replaced by its quintile rank and recoded to range from 0 to 1. The interaction term between the determinant and the *UE* variable is then created. The resulting coefficient on the interaction term can be interpreted as the increase in the magnitude of the hedge portfolio returns attributable to a move from the lowest to the highest quintile of the determinant. The final regression model we estimate is:

$$AbRet12 = \beta_0 + \beta_1\, UE\ Quintile + \sum \beta_i\, Determinant\ Quintile$$
$$+ \sum \beta_i\, UE\ Quintile \times Determinant\ Quintile + \sum \beta_k\, Control\ Variable_k + \varepsilon \quad (5)$$

where for each firm-quarter announcement, *AbRet12* is the 12-month abnormal return, *UE Quintile* is a categorical variable that ranges from 0 to 1, and *Determinant Quintile* is a categorical variable that ranges from 0 to 1 and is derived from various determinants of the PEAD.

Table 6 reports the results of the Fama-MacBeth [1973] regressions. In the first three columns, we include only our transaction cost variables. We find that the interaction terms of *ESpread*, *QSpread*, and *LDV* are statistically significant. This finding confirms results in prior tables that transaction costs have a significant effect on the PEAD. For instance, for firms within the bottom quintile of *ESpread*, the hedge portfolio returns are 1.55%. On the other hand, the hedge portfolio returns are 13.15% (= 1.55% + 11.60%) for firms in the top quintile of *ESpread*.

Column IV re-examines Mendenhall's [2004] results by using price (*Price*) and trading volume (*Volume*) as proxies for transaction costs. It also includes proxies for arbitrage risk (*Volatility*) and investor sophistication (*Institution*). Our results in column IV are generally similar to those of Mendenhall. There is evidence of an expected negative cross-sectional effect of *Volume*, but no evidence of an effect of *Price*, on the magnitude of the PEAD. In addition, there is evidence of a positive association between *Volatility* and the magnitude of the PEAD, suggesting that the PEAD is larger among firms with higher arbitrage risk.

Finally, the last three columns repeat the analysis by replacing *Price* and *Volume* with *ESpread*, *QSpread*, and *LDV*. In contrast to the results in column IV, we find that the transaction costs continue to explain the PEAD. One likely reason for the difference in the results is that we have better measures of transaction costs. For example, Lesmond et al. [1999] note that proxy variables for transaction costs such as price and volume cannot directly estimate the effects of transaction costs and that these variables may capture the effect of variables that are not related to transaction costs. In addition, we find statistically significant negative coefficients for the interaction term of *Institution*, consistent with Bartov et al.'s [2000] argument that firms whose investors are more sophisticated are likely to suffer from less mispricing.

Overall, the results in Table 6 provide evidence that transaction costs create limits to arbitrage in the PEAD setting.

5. *Additional Analyses*

5.1 THE EFFECT OF PRICE IMPACT ON THE MAGNITUDE OF THE PEAD

The literature on transaction costs has emphasized the importance of taking into account the price impact of trades because large buy (sell) trades are likely to lead to significant upward (downward) price pressure (e.g., Bhushan [1994], Keim and Madhavan [1998], Korajczyk and Sadka [2004]). For completeness, we provide evidence that the abnormal returns for the PEAD strategy are also larger for firms for which trades have large price impacts. We use two measures of price impact – *Depth* and *Volume* – as described in section 3.3.

Table 7 repeats the portfolio analysis in Table 4 after partitioning the sample based on the price impact measures of *Depth* and *Volume*. In contrast to Table 3, this table does not present profitability analyses because there is no reliable way to translate these measures of price impacts into percentage amounts. Panel A (B) presents abnormal returns for the portfolios sorted independently on *UE* and *Depth* (*Volume*). We find that the hedge portfolio returns are largely concentrated among firms for which trades have higher price impacts, consistent with limits to arbitrage created by implicit transaction costs.

5.2 PROFITABILITY OF TRADING ON REVENUE SURPRISES AND EARNINGS SURPRISES

Jegadeesh and Livnat [2006] investigate the role of revenue surprises in predicting differential drift levels and document two key findings: i) similar to the PEAD, there is a positive (negative) drift after positive (negative) revenue surprises, and ii) a trading strategy that buys (sells) firms with extreme high revenue surprises and extreme high earnings surprises (extreme low revenue surprises and extreme low earnings surprises) generates higher hedge portfolio returns than the traditional PEAD strategy that uses only earnings surprises as a signal. We investigate the profitability of this strategy after taking into account transaction costs.

Similar to our measure of earnings surprise, *UE*, we measure revenue surprise for firm *i* in quarter *q*, $UR_{i,q}$, as:[15]

$$UR_{i,q} = \frac{R_{i,q} - R_{i,q-4}}{MV_{i,q-4}} \tag{6}$$

where $R_{i,q}$ is the most recent quarterly revenue (Compustat #2), $E_{i,q-4}$ is the quarterly revenue four quarters before, and $MV_{i,q-4}$, is the market value at the end of the fiscal quarter four fiscal quarters before.

In Table 8, we provide confirming evidence of the abnormal returns documented in Jegadeesh and Livnat [2006] using a sample of 309,254 NYSE, AMEX, and NASDAQ firm-quarters from 1988 to 2005. Panels A and B present the abnormal returns, transaction costs, and profits of a trading strategy that relies only on revenue surprises as a signal. We observe from panel B that a trading strategy leveraging on revenue surprises generates abnormal returns of 6.59%. After deducting transaction costs, however, the profitability of the trades is negative. Panels C and D present similar analyses for the trading strategy that uses both revenue surprises (*UR*) and earnings surprises (*UE*). For parsimony, we only show the transaction costs of the extreme portfolios in panel D. Once again, we observe that profitability is significantly reduced by transaction costs. For

[15] Consistent with our definition of earnings surprise, we assume that expected revenue follows a seasonal random walk, and we scale revenue surprise by market value. The main measure of revenue surprise in Jegadeesh and Livnat [2006] assumes that expected revenue follows a seasonal random walk with drift, and they scale revenue surprise by the standard deviation of prior revenue surprises. Our conclusion that transaction costs significantly reduce profitability is robust to this alternative measure.

example, the hedge portfolio return for a trading strategy that buys (sells) firms in *UR* quintile 5 and *UE* quintile 5 (*UR* quintile 1 and *UE* quintile 1) generates abnormal returns of 12.92%. The profit after deducting *ESpread* (*LDV*) is 1.73% (-2.55%).

5.3 ANALYST EXPECTATIONS AS A BENCHMARK FOR EXPECTED EARNINGS

The analyses so far were done by measuring earnings surprises as seasonal changes in quarterly earnings. A more recent literature, however, has documented larger abnormal returns with a variation of the PEAD strategy that uses analyst expectations as the benchmark for expected earnings (Livnat and Mendenhall [2006], Doyle et al. [2006]). This finding provides a tougher hurdle for the transaction cost explanation. First, analysts' forecasts allow for a more precise measure of earnings surprise than a time-series model, which should increase attainable returns. Second, firms followed by analysts have lower transaction costs. Thus, we assess the robustness of our results to the PEAD strategy documented by this recent literature. We use the *Analyst UE* variable described in section 4.2 as a proxy for earnings surprises. We then repeat the profitability analyses by forming portfolios based on *Analyst UE.*

Table 9 presents the profitability analyses for 213,022 NYSE, AMEX, and NASDAQ firm-quarters for the sample period from 1988 to 2005. Panel A presents the analyses using equal-weighted returns. Panel A shows that firms in the top (bottom) *Analyst UE* decile generate 3-month size-adjusted returns of 3.97% (-2.36%) and 12-month size-adjusted returns of 12.12% (-1.58%). This implies that a PEAD strategy that buys (sells) firms in the top (bottom) *Analyst UE* decile generates 3-month size-adjusted returns of 6.33% and 12-month size-adjusted returns of 13.70%. The strategy, however, earns 3-month (12-month) profits of -1.60%, -4.38%, and -4.57% (5.76%, 2.99%, and 2.80%) after deducting *ESpread*, *QSpread*, and *LDV*, respectively.

With value-weighted returns (panel B), the 3-month (12-month) abnormal hedge portfolio returns are 2.66% (6.75%). In this case, the deduction of transaction costs reduces the 3-month (12-month) profitability of the PEAD strategy to -0.36%, -1.85%, and -2.02% (3.73%, 2.24%, and 2.07%) after deducting effective spreads, quoted spreads, and *LDV*, respectively. Hence, although transaction costs can account for a significant portion of the abnormal returns documented in Livnat and Mendenhall [2006] and Doyle et al. [2006], economically and statistically significant abnormal returns remain for buy-hold periods of twelve months.

Given that this innovation has only recently appeared in the academic literature, a potential explanation is that insufficient informed trading has developed for prices to move fully to the transaction cost bound. In Figure 1, we present evidence of the abnormal returns from the PEAD strategy using I/B/E/S analyst expectations. Consistent with the literature, we find that the abnormal returns are consistently positive, suggesting that a risk explanation for the drift is less likely (Bernard and Thomas [1989, 1990] Doyle et al. [2006]). An interesting observation from Figure 1 is that the magnitude of the abnormal returns appears to have declined over time and have converged to the magnitude of the transaction costs.[16] A possible inference is that more informed trading at the time of the earnings announcement has led to smaller post-announcement abnormal returns, but the abnormal returns are not zero due to the constraints to price discovery created by transaction costs.

[16] The rise in transaction costs seems counterintuitive. However, this is due to a composition effect, the inclusion of many smaller firms. If we constrain the sample to the S&P 500 we find the expected trend of declining transaction costs over time.

6. *Conclusion*

In this paper, we study how transaction costs can offer an explanation for the existence of the PEAD. First, we explain how an underreaction to earnings news can occur because transaction costs constrain the profitable trades by informed investors that are necessary to incorporate earnings information into price. This explanation leads to our first prediction that the market reaction to earnings surprises will be smaller for firms whose shares have higher transaction costs. We then explain how profitable trades made by informed investors can lead to a post-announcement drift in returns and we predict that the drift in returns after earnings surprises will be larger for firms whose shares have higher transaction costs

Our results are generally consistent with our hypotheses. First, we find that earnings response coefficients are lower for firms with higher transaction costs. Second, using portfolio analyses, we find that the profits of implementing the PEAD trading strategy are significantly reduced by transaction costs. In addition, we show, using a combination of portfolio and regression analyses, that firms with higher transaction costs are the ones that provide the higher abnormal returns. Further, we provide evidence that the higher abnormal returns among firms with higher transaction costs do not result in higher profitability once transaction costs are accounted for.

The analyses in this paper can equally be applied to other accounting-based anomalies, especially if the anomaly involves investing in firms with extreme characteristics that are indicative of high transaction costs. Our work also has implications for the nascent literature on directly testing behavioral theories (e.g., Chan, Frankel, and Kothari [2005]). Limits to arbitrage suggest that the largest mispricing will occur in those stocks that are costly to arbitrage. This means that when transaction costs are low, we might see little mispricing even if the behavioral theory applies to the vast majority of investors, because any mispricing is quickly arbitraged away. In contrast, when transaction costs are high, the behavioral bias will be reflected in share prices, as arbitrageurs will abstain from trading until the mispricing becomes large enough to make a profit. Therefore, small firms, firms with high transaction costs, and firms with low institutional ownership may provide for a more powerful sample to test behavioral theories than a generic sample of firms.

REFERENCES

Ball, R. “The Earnings-Price Anomaly.” *Journal of Accounting and Economics* 15 (1992): 319-345.

Ball, R., and P. Brown. “An Empirical Evaluation of Accounting Numbers.” *Journal of Accounting Research* 6 (1968): 159-178.

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

Bartov, E.; I. Krinsky; and S. Radhakrishnan. “Investor Sophistication and Patterns in Stock Returns after Earnings Announcements.” *The Accounting Review* 75 (2000): 43-63.

Bernard, V. L., and J. K. Thomas. “Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?” *Journal of Accounting Research* 27 (1989): 1–48.

Bernard, V. L., and J. K. Thomas. “Evidence that Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings.” *Journal of Accounting and Economics* 13 (1990): 305-340.

Bessembinder, H. “Trade Execution Costs and Market Quality After Decimalization.” *Journal of Financial and Quantitative Analysis* 38 (2003): 747-777.

Bhardwaj, R. K., and L. D. Brooks. “The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias.” *Journal of Finance* 47 (1992): 553-575.

Bhushan, R. “An Informational Efficiency Perspective on the Post-Earnings Announcement Drift.” *Journal of Accounting and Economics* 18 (1994): 45-65.

Brown, L.; R. Hagerman; P. Griffin; and M. Zmijewski. “An Evaluation of Alternative Proxies for the Market's Assessment of Unexpected Earnings.” *Journal of Accounting and Economics* 9 (1987): 159-193.

Chan, W. A.; R. Frankel; and S.P. Kothari. “Testing Behavioral Finance Theories Using Trends and Sequences in Financial Performance.” Working paper, Massachusetts Institute of Technology, 2005.

Chordia, T.; A. Goyal; G. Sadka; R. Sadka; and L. Shivakumar. “Liquidity and Post-Earnings-Announcement-Drift.” Working paper, Emory University, 2007.

Collins, D. W., and S. P. Kothari. “An Analysis of Inter-temporal and Cross-sectional Determinants of Earnings Response Coefficients.” *Journal of Accounting and Economics* 11 (1989): 143–181.

Diamond, D. W., and R. E. Verrecchia. "Constraints on Short-selling and Asset Price Adjustment to Private Information." *Journal of Financial Economics* 18 (1987): 277-311.

Dichev, I., and J. Piotroski. "The Long-run Stock Returns Following Bond Ratings Changes." *Journal of Finance* 56 (2001): 173-203.

Doyle, J. T.; R. J. Lundholm; and M. T. Soliman. "The Extreme Future Stock Returns Following I/B/E/S Earnings Surprises." *Journal of Accounting Research* 44 (2006): 849-888.

Easton, P. D., and M. E. Zmijewski. "Cross-sectional Variation in the Stock Market Response to Accounting Earnings Announcements." *Journal of Accounting and Economics* 11 (1989): pp. 117–141.

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

Fama, E., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (1973): 607–636.

Foster, G.; C. Olsen; and T. Shevlin. "Earnings Releases, Anomalies and the Behavior of Security Returns." *The Accounting Review* 59 (1984): 574–603.

Garman, M. B., and J. A. Ohlson. "Valuation of Risky Assets in Arbitrage Free Economies with Transaction Costs." *Journal of Financial Economics* 9 (1980): 271-280.

Gleason, C., and C. Lee. "Analyst Forecast Revisions and Market Price Discovery." *The Accounting Review* 78 (2003): 193-225.

Glosten, L., and P. Milgrom. "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics* 14 (1985): 71-100.

Hanna, J. D., and M. J. Ready. "Profitable Predictability in the Cross Section of Stock Returns." *Journal of Financial Economics* 78 (2005): 463-505.

Hasbrouck, J. "The Summary Informativeness of Stock Trades: An Econometric Analysis." *The Review of Financial Studies* 4 (1991): 571-594.

Hirshleifer, D. "Investor Psychology and Asset Pricing." *Journal of Finance* 56 (2001): 1533-1598.

Huang, R., and H. Stoll. "The Components of Bid-Ask Spread: A General Approach." *Review of Financial Studies* 10 (1997): 995-1034.

Ikenberry, D., J. Lakonishok; and T. Vermaelen. "Market Underreaction to Open Market Share Repurchases." *Journal of Financial Economics* 39 (1995): 181-208.

Ikenberry, D., G. Rankine; and E. K. Stice. "What Do Stock Splits Really Signal?" *Journal of Financial and Quantitative Analysis* 31 (1996): 357-375.

Jegadeesh, N., and J. Livnat. "Revenue Surprises and Stock Returns." *Journal of Accounting and Economics* 41 (2006): 147-171,

Ke, B., and S. Ramalingegowda. "Do Institutional Investors Exploit the Post-Earnings Announcement Drift?" *Journal of Accounting and Economics* 39 (2005): 25-53.

Keim, D. B., and A. Madhavan. "The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects." *Review of Financial Studies* 9 (1996): 1-36.

Keim, D. B., and A. Madhavan. "The Cost of Institutional Equity Trades." *Financial Analysts Journal* 54 (1998): 50-69.

Kim, O., and R. E. Verrecchia. "Liquidity and Volume Around Earnings Announcements." *Journal of Accounting and Economics* 17 (1994): 41-67.

Knez, P. J., and M. J. Ready. "Estimating the Profits from Trading Strategies." *The Review of Financial Studies* 9 (1996): 1121-1163.

Korajczyk, R., and R. Sadka. "Are Momentum Profits Robust to Trading Costs?" *Journal of Finance* 59 (2004): 1039-1082.

Kothari, S. P. and R. G. Sloan. "Information in prices about future earnings: implications for earnings response coefficients." *Journal of Accounting and Economics* 15 (1992): 143–171.

Krinsky, I., and J. Lee. "Earnings Announcement and the Components of the Bid-Ask Spread." *Journal of Finance* 51 (1996): 1523-1535.

Kyle, A. S. "Continuous Auctions and Insider Trading." *Econometrica* 53 (1985): 1315-1336.

Lee, C. M. C. "Earnings News and Small Traders." *Journal of Accounting and Economics* 15 (1992): 265-302.

Lee, C. M. C. "Market Efficiency and Accounting Research: a Discussion of 'Capital Market Research in Accounting' by S.P. Kothari." *Journal of Accounting and Economics* 31 (2001): 233-253.

Lee, C. M. C.; B. Mucklow; and M. J. Ready. “Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis.” *Review of Financial Studies* 6 (1993): 345-374.

Lee, C. M. C., and M. J. Ready. “Inferring Trading Direction from Intraday Data.” *Journal of Finance* 51 (1991): 1523-1535.

Lesmond, D. A.; J. P. Ogden; and C. A. Trzcinka. “A New Estimate of Transaction Costs.” *The Review of Financial Studies* 12 (1999): 1113-1141.

Lesmond, D. A.; M. J. Schill; and C. Zhou. “The Illusory Nature of Momentum Profits.” *Journal of Financial Economics* 71 (2004): 349-380.

Livnat, J., and R. R. Mendenhall. “Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts.” *Journal of Accounting Research* 44 (2006): 177-205.

Lo, A. W.; H. Mamaysky; and J. Wang. “Asset Prices and Trading Volume under Fixed Transaction Costs.” *Journal of Political Economy*112 (2004): 1054-1090.

Mendenhall, R. R. “Arbitrage Risk and Post-Earnings-Announcement Drift.” *Journal of Business* 77 (2004): 875-894.

Pástor, Ľ., and R. F. Stambaugh. “Liquidity Risk and Expected Stock Returns.” *Journal of Political Economy* 111 (2003): 642-685.

Pontiff, J. “Costly Arbitrage and the Myth of Idiosyncratic Risk.” *Journal of Accounting and Economics* 42 (2006): 35-52.

Sadka, G., and R. Sadka. “The Post-Earnings-Announcement Drift and Liquidity Risk.” Working paper, Columbia University, 2004.

Sadka, R. “Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk.” *Journal of Financial Economics* 80 (2006): 309-349.

Smith, B. F.; D. A. S. Turnbull; and R. W. White. “Upstairs Market for Principal and Agency Trades: Analysis of Adverse Selection and Price Effects.” *Journal of Finance* 56 (2001): 1723-1746.

Appendix 1

1.A – Cleaning the Institute for the Study of Security Markets (ISSM) database

We use the intra-day quotes and trades from the ISSM database, which consists of a trades file and a quotes file, to compute the market microstructure variables from January 1988 to December 1992. To ensure data integrity, we remove the errors and outliers from the files.

For the trades file, we retain the following:

1. Trades inside regular trading hours (9:30-16:00)
2. Regular sale conditions (cond = blank)
3. Trades with positive trade price (price > 0) and positive trade size (siz > 0)
4. Trades with absolute change in trade price from the previous trade price of less than or equal to 10%

For the quotes file, we retain the following:

1. Quotes inside regular trading hours (9:30-16:00)
2. Regular quotes (mode = blank)
3. Quotes with positive bid price (bid > 0), positive ask price (ofr > 0), ask price greater than bid price (ofr > bid), positive bid size (bidsiz > 0) or positive ask size (ofrsiz > 0)
4. Quotes with relative quoted spreads less than or equal to 20%
5. Quotes with absolute change in bid price from the previous bid price in each day of less than or equal to 10% and with absolute change in ask price from the previous ask price in each day of less than or equal to 10%.
6. For the computation of relative effective spreads only, quotes with relative effective spreads less than or equal to 20%

1.B – Cleaning the NYSE Trades and Quotes (TAQ) database

We use the intra-day quotes and trades from the NYSE TAQ database, which consists of a trades file and a quotes file, to compute the market microstructure variables from January 1993 to December 2003. To ensure data integrity, we remove the errors and outliers from the files.

For the trades file, we retain the following:

1. Trades inside regular trading hours (9:30-16:00)
2. Good trades (corr = 0, 1)
3. Regular sale conditions (cond = blank or *)
4. Trades with positive trade price (price > 0) and positive trade size (siz > 0)
5. Trades with absolute change in trade price from the previous trade price of less than or equal to 10%

For the quotes file, we retain the following:

1. Quotes inside regular trading hours (9:30-16:00)
2. Regular quotes (mode = 12)
3. Quotes with positive bid price (bid > 0), positive ask price (ofr > 0), bid price greater than ask price (ofr > bid), positive bid size (bidsiz > 0) or positive ask size (ofrsiz > 0)
4. Quotes with relative quoted spreads less than or equal to 20%
5. Quotes with absolute change in bid price from the previous bid price in each day of less than or equal to 10% and with absolute change in ask price from the previous ask price in each day of less than or equal to 10%.
6. For the computation of relative effective spreads only, quotes with relative effective spreads less than or equal to 20%

1.C Matching of trades and quotes

The matching of trades and quotes is required for the computation of effective spreads. In combining the trades and quotes, we take the following steps. Following Lee and Ready [1991], we match each trade with the latest available quote at least five seconds earlier. Then, as in Huang and Stoll [1997], we collapse all trades that took place at the same price and quotes (bid price and ask price) into a single trade. According to Huang and Stoll, "a large order may be executed at a single price but be reported in a series of smaller trades" and "a single large limit order may be executed at a single price against various incoming market orders".

1.D Calculation of LDV measure

The LDV measure is based on the transaction costs implied by the trading behavior of investors and is more fully explained in Lesmond, Ogden, and Trzcinka [1999]. It is assumed that informed investors do not trade when the cost of trading exceeds the value of the information. When this is the case, we would expect zero return on the stock. Since private information is not observable and cannot be used to calculate the implied transaction cost, the model uses the information in the market return to make its inferences. The correct model for security returns is assumed to be the market model, but trades are constrained by transaction costs. Thus the true returns of the firm will deviate from the measured return in cases where the value of information is too low to justify the transaction costs.

This leads to the following model of the relation between transaction costs and the return of the security. First the relation between the true return and the market return follows the standard market model:

$$R^*_{jt} = \beta_j * R_{mt} + \varepsilon_{jt}$$

Second, the relation between the measured return, R_{jt}, and the true return, R^*_{jt}, on the security is described by the following system:

$$R_{jt} = R^*_{jt} - \alpha_{1j}, \ldots . if .. R^*_{jt} < \alpha_{1j}$$
$$R_{jt} = 0, \ldots\ldots\ldots\ldots\ldots . if .. \alpha_{1j} < R^*_{jt} < \alpha_{2j}$$
$$R_{jt} = R^*_{jt} - \alpha_{2j}, \ldots if .. R^*_{jt} > \alpha_{2j}$$

For firm j, the transaction cost threshold is α_{1j} for trades on negative information and α_{2j} for trades on positive information. The difference between the two thresholds, $\alpha_{2j} - \alpha_{1j}$, provides an estimate of the roundtrip transaction costs.

The model can be estimated by maximum likelihood once we make a distributional assumption for the error term. Following standard finance literature, the model assumes daily returns are distributed normally. The model is then estimated using the following log likelihood function.

$$\ln L = \sum_1 \ln \frac{1}{(2\pi\sigma_j^2)^{1/2}} - \sum_1 \frac{1}{2\sigma_j^2}\left(R_{jt} + \alpha_{1j} - \beta * R_{mt}\right)^2$$
$$+ \sum_2 \ln \frac{1}{(2\pi\sigma_j^2)^{1/2}} - \sum_2 \frac{1}{2\sigma_j^2}\left(R_{jt} + \alpha_{2j} - \beta * R_{mt}\right)^2$$
$$+ \sum_0 \ln\left(\Phi_2\left(\frac{\alpha_{2j} - \beta_j * R_{mt}}{\sigma_j}\right) - \Phi_1\left(\frac{\alpha_{1j} - \beta_j * R_{mt}}{\sigma_j}\right)\right)$$

The measure has two main advantages. First, when the model's assumptions are satisfied, the measure incorporates all costs that are important to traders and that are reflected in their trading behavior. This is important because several aspects of transaction costs are hard to estimate directly. Second, the measure is relatively easy to compute and is available for any period for which daily stock returns from CRSP are available.

The main disadvantage of the measure is that the estimates are based on a model and thus the estimates are only as good as the model that produces them. In particular, the model assumes that all impediments to efficient market reaction are due to transaction costs. To the extent that there are other behavioral or institutional factors leading to an underreaction to market level news, the LDV estimate of transaction costs might be overstated. A potentially mitigating factor is that Lesmond et al. [1999] find that the measure is highly correlated with directly observable measures of transaction costs.

This potential overestimate might also affect our regression analysis. However, here there are two additional mitigating factors. First, this potential overestimate only biases the coefficients on the interaction terms upwards if the same forces that lead to underreaction relative to the market news also lead to an underreaction to earnings news. If not, then it is just noise which would generally lead to an attenuation bias. Second, our control variables, such as the percentage of institutional holdings, at least partially control for these other behavioral or institutional factors as well.

Table 1 – Characteristics of UE Deciles

Panel A presents firm characteristics for each Unexpected Earnings (*UE*) decile. Panels B and C present the trade-related characteristics for each *UE* decile. Panel D presents the distribution of daily spreads during the earnings announcement month. The sample size is 126,386 firm-quarter earnings announcements from NYSE and AMEX from 1988 to 2005. *Beta* is estimated from a market model regression for each firm using at least 18 monthly returns over the five years before the announcement month. *Size* is the market value of equity at the end of the previous fiscal quarter. *BEME* is the ratio between the book value and the market value of equity at the end of the previous fiscal quarter. *Institution* is the fraction of shares held by institutional investors at the end of the calendar quarter before the earnings announcement. *Volatility* is the standard deviation of the residuals of a regression of daily returns on the S&P500 returns during the 12-month period ending in the announcement month. *Price* is the average close daily price in the announcement month. *AbRet3* (*AbRet12*) is the 3-month (12-month) size-adjusted returns from the month following the announcement month. *Commission* is the average daily commission in the announcement month. *ESpread* is the average daily effective spread plus commissions in the announcement month. *QSpread* is the average daily quoted spread plus commissions in the announcement month. *LDV* is the comprehensive estimate of transaction costs developed by Lesmond et al. [1999]. *Depth* is the average daily quoted depth in the announcement month. *Volume* is the average daily dollar trading volume in the announcement month. *Trade Size* is the average daily trade size in the announcement month. *Few Trades* is the fraction of firm-quarters within each *UE* decile with an average of five or fewer daily trades in the announcement month. In panel D, Q1, median, and Q3 spreads are the first quartile, the median, and the third quartile of the daily spreads in the announcement month.

Panel A – Firm characteristics

Decile	*Beta*	*Size* ($M)	*Log BEME*	*Institution*	*Volatility*	*Price* ($)
1	0.95	1,896.8	-0.39	0.40	0.11	18.52
2	0.89	2,697.4	-0.53	0.43	0.10	23.07
3	0.84	3,704.0	-0.70	0.45	0.09	27.20
4	0.85	5,383.5	-0.85	0.48	0.08	31.69
5	0.88	4,973.5	-0.86	0.50	0.09	32.82
6	0.89	3,780.1	-0.78	0.49	0.09	30.59
7	0.93	2,887.1	-0.65	0.46	0.10	27.05
8	0.97	2,294.1	-0.54	0.42	0.12	23.08
9	1.03	1,193.2	-0.36	0.34	0.15	15.49
10	0.91	3,194.7	-0.61	0.44	0.11	24.69
All	0.95	1,896.8	-0.39	0.40	0.11	18.52

Table 1 – Cont'd

Panel B – Size-adjusted returns and transaction costs (all numbers are in %)

Decile	*AbRet3*	*AbRet12*	*Commission*	*ESpread*	*QSpread*	*LDV*
1	-2.16	-4.59	2.78	4.53	6.48	5.69
2	-1.44	-0.17	1.64	2.80	4.33	3.63
3	-1.00	-0.38	1.18	2.12	3.37	2.77
4	-0.70	-0.19	0.93	1.73	2.80	2.26
5	-0.28	0.31	0.77	1.48	2.43	1.93
6	0.55	1.75	0.76	1.45	2.39	1.93
7	0.81	2.92	0.86	1.60	2.61	2.19
8	1.62	4.06	1.04	1.89	3.00	2.68
9	1.73	5.38	1.40	2.43	3.74	3.58
10	3.23	7.33	2.45	4.04	5.78	6.05
All	0.27	1.69	1.00	2.31	3.60	3.10

Panel C – Price impact and other trade characteristics

Decile	*Depth* ($K)	*Volume* ($K)	*Trade Size* ($K)	*Few Trades*
1	49.41	1,008.1	11.84	0.26
2	65.76	1,857.7	16.32	0.18
3	76.69	2,638.5	21.01	0.14
4	88.49	3,633.5	26.45	0.12
5	98.02	5,289.4	27.73	0.09
6	94.09	4,891.7	30.34	0.09
7	85.00	3,732.6	23.58	0.10
8	78.73	2,863.3	22.41	0.12
9	69.22	2,271.8	16.56	0.15
10	53.29	1,180.2	12.77	0.21
All	74.07	3,143.4	20.48	0.13

Panel D – Distribution of *ESpread* and *QSpread* (all numbers are in %)

Decile	*ESpread*			*QSpread*		
	Q1	Median	Q3	Q1	Median	Q3
1	4.15	4.99	6.10	6.08	6.90	8.01
2	2.55	3.06	3.71	4.05	4.57	5.22
3	1.94	2.31	2.75	3.17	3.55	4.01
4	1.59	1.88	2.23	2.64	2.95	3.33
5	1.36	1.59	1.87	2.28	2.54	2.84
6	1.32	1.56	1.83	2.25	2.50	2.80
7	1.47	1.73	2.06	2.45	2.74	3.08
8	1.73	2.04	2.43	2.81	3.15	3.55
9	2.22	2.64	3.17	3.50	3.93	4.49
10	3.73	4.45	5.42	5.45	6.16	7.12

Table 2 – Market Reaction to Earnings Surprises

This table presents the results of earnings response coefficient regressions to examine the market reaction to earnings surprises. *AbRet3d* is the 3-day size-adjusted returns around the earnings announcement date. *AbRet4q* is the size-adjusted returns cumulated from the second day after the earnings announcement four fiscal quarters ago until the first day after the earnings announcement for the current fiscal quarter. *Surprise* is the earnings surprise measured either as *UE* or *Analyst UE*. *UE* is the earnings surprise (*Surprise*) measured using earnings expectation from a seasonal random walk model. *Analyst UE* is the alternative measure of *Surprise* using median I/B/E/S consensus analyst forecasts as the earnings expectation. All other variables are defined in Table 1. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

	Dependent Variable								
	AbRet3d			*AbRet4q*			*AbRet3d*		
	Surprise = UE						*Surprise = Analyst UE*		
	I	II	III	IV	V	VI	VII	VIII	IX
Intercept	0.01***	0.01***	0.00	0.50***	0.49***	0.14***	0.01***	0.01***	0.00
	9.71	*9.60*	*0.49*	*28.35*	*28.24*	*10.08*	*6.54*	*7.50*	*1.58*
Surprise	0.18***	0.21***	0.34***	6.96***	7.46***	2.99***	2.60***	2.23***	2.04***
	4.30	*5.52*	*9.21*	*13.00*	*12.79*	*8.84*	*6.35*	*7.11*	*8.76*
*Surprise * Beta*	-0.01	-0.01	0.00	0.61***	0.69***	0.47**	0.12	0.10	0.15*
	-0.47	*-0.45*	*-0.07*	*3.20*	*3.53*	*2.38*	*1.46*	*1.23*	*1.68*
*Surprise * Log (Size)*	-0.12***	-0.15***	-0.24***	-2.17***	-2.49***	1.28***	0.03	0.26	0.51**
	-3.02	*-4.10*	*-7.49*	*-4.92*	*-6.06*	*3.72*	*0.09*	*0.89*	*2.23*
*Surprise * Log BEME*	0.03	0.03	0.03	-2.11***	-2.05***	-2.16***	-0.37***	-0.40***	-0.41***
	1.25	*1.32*	*1.17*	*-7.83*	*-7.60*	*-8.08*	*-3.58*	*-3.68*	*-3.94*
*Surprise * ESpread*	0.04			-4.02***			-1.68***		
	1.28			*-8.45*			*-4.56*		
*Surprise * QSpread*		0.01			-4.65***			-1.27***	
		0.23			*-9.87*			*-4.77*	
*Surprise * LDV*			-0.13***			0.15			-1.11***
			-5.41			*0.42*			*-6.18*
Main effect for Determinant included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.03	0.03	0.03	0.19	0.19	0.17	0.04	0.04	0.04
OBS	126,386	126,386	126,386	126,386	126,386	126,386	95,299	95,299	95,299

Table 3 – Profitability Analyses for PEAD Trading Strategy

Panel A (Panel B) presents the profitability analysis using equal-weighted (value-weighted) abnormal returns and transaction costs. The sample size is 126,386 firm-quarter earnings announcements from NYSE and AMEX from 1988 to 2005. *AbRet3* (*AbRet12*) is the 3-month (12-month) size-adjusted returns from the month following the announcement month. *ESpread* is the average daily effective spread plus commissions in the announcement month. *QSpread* is the average daily quoted spread plus commissions in the announcement month. *QProfit3* (*QProfit12*) is *AbRet3* (*AbRet12*) minus *QSpread*. *EProfit3* (*EProfit12*) is *AbRet3* (*AbRet12*) minus *ESpread*. *LDVProfit3* (*LDVProfit12*) is *AbRet3* (*AbRet12*) minus *LDV*. All other variables are defined in Table 1. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A – Equal-weighted profitability

	Three-month holding period				Twelve-month holding period			
	AbRet3	*EProfit3*	*QProfit3*	*LDVProfit3*	*AbRet12*	*EProfit12*	*QProfit12*	*LDVProfit12*
Short 1	-2.16	-2.37	-4.32	-3.54	-4.59	0.06	-1.89	-1.10
Buy 10	3.23	-0.81	-2.56	-2.82	7.33	3.29	1.55	1.29
Hedge	5.38***	-3.18***	-6.88***	-6.35***	11.92***	3.36***	-0.34	0.19
t-stat	8.99	-5.36	-10.98	-9.50	9.38	2.79	-0.28	0.15

Panel B – Value-weighted profitability

	Three-month holding period				Twelve-month holding period			
	AbRet3	*EProfit3*	*QProfit3*	*LDVProfit3*	*AbRet12*	*EProfit12*	*QProfit12*	*LDVProfit12*
Short 1	0.38	-1.50	-2.24	-2.20	0.49	-1.62	-2.36	-2.31
Buy 10	0.47	-0.53	-1.22	-1.30	2.84	1.84	1.15	1.07
Hedge	0.09	-2.04***	-3.47***	-3.50***	2.35*	0.22	-1.21	-1.24
t-stat	0.12	-2.69	-4.47	-4.60	1.67	0.16	-0.86	-0.88

Table 4 – Profitability Analyses for UE and Transaction Cost Portfolios

This table presents the 12-month size-adjusted returns and transaction costs for portfolios sorted independently on unexpected earnings and transaction costs. Panels A, B and C present the analysis using *ESpread*, *QSpread*, and *LDV*, as the respective measures of transaction costs. The sample size is 126,386 firm-quarter earnings announcements from NYSE and AMEX from 1988 to 2005. All variables are defined in Table 1. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A – Partition by *ESpread*

	ESpread Quintile				
UE Quintile	1	2	3	4	5
AbRet12					
1	-0.17	-0.58	0.09	-1.13	-4.84
5	2.90	1.24	4.88	7.55	9.78
5-1 Return	3.07***	1.82*	4.79***	8.68***	14.61***
ESpread					
1	0.62	0.97	1.45	2.37	6.76
5	0.61	0.98	1.44	2.35	6.83
5-1 Profit	1.84*	-0.14	1.90*	3.95***	1.02

Panel B – Partition by *QSpread*

	QSpread Quintile				
UE Quintile	1	2	3	4	5
AbRet12					
1	-0.29	-0.16	0.05	-0.95	-4.93
5	3.89	1.16	6.31	6.19	9.92
5-1 Return	4.17***	1.32	6.26***	7.14***	14.85***
QSpread					
1	1.05	1.67	2.45	3.93	9.51
5	1.04	1.66	2.44	3.89	9.60
5-1 Profit	2.09**	-2.01*	1.37	-0.67	-4.26**

Panel C – Partition by *LDV*

	LDV Quintile				
UE Quintile	1	2	3	4	5
AbRet12					
1	-0.72	-0.38	-0.73	-1.90	-4.10
5	2.31	2.18	3.76	6.59	9.90
5-1 Return	3.03**	2.56**	4.49***	8.49***	14.00***
LDV					
1	0.76	1.44	2.11	3.36	8.48
5	0.74	1.45	2.11	3.33	9.00
5-1 Profit	1.53	-0.34	0.28	1.80	-3.48**

Table 5 – Annualized Alphas and Profits for UE and Transaction Cost Portfolios

This table presents annualized alphas and profits for a hedge portfolio that buys (sells) firms in the top (bottom) quintile of unexpected earnings. The sample size is 126,386 firm-quarter earnings announcements from NYSE and AMEX from 1988 to 2005. The annual alphas and profits are computed for each of the five quintiles of transaction costs. Panels A, B and C present the analysis using *ESpread*, *QSpread*, and *LDV* as the respective measures of transaction costs. FF 3-factor alpha (Carhart 4-factor alpha) is the estimated intercept of a regression of the portfolio monthly excess return on the market premium, SMB, and HML (market premium, SMB, HML, and the momentum factor – UMD), multiplied by 12. PS 4-factor alpha is the estimated intercept of a regression of the portfolio monthly excess return on the market premium, SMB, HML, and the Pastor and Stambaugh [2003] liquidity factor, multiplied by 12. In panels A, B, and C, the corresponding factor profit numbers are the alphas minus the transaction costs estimated using *ESpread*, *QSpread*, and *LDV*, respectively. All variables are defined in Table 1. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A – Partition by *ESpread*

	ESpread Quintile				
	1	2	3	4	5
FF 3-factor alpha	2.78*	1.66	5.81***	8.60***	11.74***
PS 4-factor alpha	2.47	1.50	5.77***	8.48***	11.48***
FF 3-factor profit	1.53	-0.35	2.73	3.51*	-2.89
PS 4-factor profit	1.21	-0.53	2.66	3.31*	-3.31

Panel B – Partition by *QSpread*

	QSpread Quintile				
	1	2	3	4	5
FF 3-factor alpha	3.30*	1.47	6.21***	7.69***	11.85***
PS 4-factor alpha	3.01*	1.30	6.23***	7.63***	11.53***
FF 3-factor profit	1.22	-1.94	1.08	-0.60	-8.53***
PS 4-factor profit	0.90	-2.14	1.06	-0.76	-9.04***

Panel C – Partition by *LDV*

	LDV Quintile				
	1	2	3	4	5
FF 3-factor alpha	2.10	2.70*	5.00***	8.76***	10.75***
PS 4-factor alpha	1.82	2.51*	4.71***	8.66***	10.38***
FF 3-factor profit	0.48	-0.39	0.35	1.28	-8.81***
PS 4-factor profit	0.18	-0.61	0.00	1.09	-9.43***

Table 6 – Determinants of PEAD – Fama-MacBeth Regressions

This table presents mean estimated coefficients and t-statistics for 72 quarterly regressions of 12-month size-adjusted returns (*AbRet12*) on measures of firm characteristics, transaction costs, and price impact. The sample size is 126,386 firm-quarter earnings announcements from NYSE and AMEX from 1988 to 2005. All variables are defined in Table 1. The variables are ranked into quintiles every year and then recoded from 0 to 1. T-statistics are presented in italics below the estimated coefficients. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

	I	II	III	IV	V	VI	VII
Intercept	5.04***	5.61***	1.95	-3.08	3.70**	3.03*	-0.80
	3.90	*3.94*	*1.30*	*-1.59*	*2.32*	*1.88*	*-0.50*
Beta	0.84	0.91	0.89	0.71	0.75	0.74	0.80
	0.64	*0.69*	*0.70*	*0.67*	*0.68*	*0.67*	*0.72*
Log Size	-0.38*	-0.46**	-0.09	0.08	-0.35*	-0.35*	-0.01
	-1.91	*-2.16*	*-0.48*	*0.25*	*-1.68*	*-1.71*	*-0.07*
Log BEME	2.47***	2.49***	2.38***	2.07***	2.29***	2.29***	2.18***
	3.59	*3.64*	*3.50*	*3.22*	*3.41*	*3.42*	*3.25*
UE Quintile	1.55	2.02*	1.87*	10.83***	2.96*	4.36***	4.63***
	1.45	*1.87*	*1.87*	*5.00*	*1.87*	*2.99*	*3.52*
*ESpread Quintile * UE Quintile*	11.60***				7.73***		
	6.86				*3.65*		
*QSpread Quintile * UE Quintile*		10.76***				5.54***	
		6.25				*2.68*	
*LDV Quintile * UE Quintile*			10.94***				7.27***
			6.40				*3.15*
*Price Quintile * UE Quintile*				-3.95			
				-1.63			
*Volume Quintile * UE Quintile*				-4.31**			
				-2.32			
*Institution Quintile * UE Quintile*				-1.96	-2.63	-4.00**	-3.79**
				-1.11	*-1.47*	*-2.43*	*-2.34*
*Volatility Quintile * UE Quintile*				4.38*	3.06*	3.87**	1.63
				1.92	*1.72*	*2.15*	*0.76*
Main effect for Interaction included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.03	0.03	0.03	0.03	0.04	0.04	0.04

Table 7 – Returns Analyses for UE and Price Impact Portfolios

This table presents twelve-month size-adjusted returns for portfolios sorted independently on unexpected earnings and price impact measures. The sample size is 126,386 firm-quarter earnings announcements from NYSE and AMEX from 1988 to 2005. Panels A and B present the analysis using *Depth* and *Volume*, respectively. All variables are defined in Table 1. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A – Partition by *Depth*

	Depth Quintile				
UE Quintile	1	2	3	4	5
1	-3.09	-3.27	-1.34	-1.08	-0.40
5	9.17	7.92	4.85	3.12	3.72
5-1 Return	12.26***	11.19***	6.19***	4.20***	4.12***

Panel B – Partition by *Volume*

	Volume Quintile				
UE Quintile	1	2	3	4	5
1	-4.91	-1.82	-0.68	0.20	1.05
5	8.32	10.63	3.97	0.81	3.03
5-1 Return	13.23***	12.45***	4.66***	0.61	1.98*

Table 8 – Profitability Analyses for UR and UE Trading Strategies

This table presents profitability analyses for trading strategies based on unexpected revenue (*UR*) and unexpected earnings (*UE*) portfolios. The sample size is 309,254 firm-quarter earnings announcements from NYSE, AMEX, and NASDAQ from 1988 to 2005. Panel A presents the abnormal returns and transaction cost estimates for the *UR* deciles. Panel B presents the profitability analyses for a trading strategy that buys (sells) firms within the highest (lowest) *UR* decile. Panel C presents the 12-month size-adjusted returns for five-by-five portfolios sorted independently on *UR* and *UE*. Panel D presents the profitability analysis for a trading strategy that buys (sells) firms in *UR* quintile 5 and *UE* quintile 5 (*UR* quintile 1 and *UE* quintile 1). In this panel, *ESpread*, *QSpread*, and *LDV* are used as different measures of transaction costs. All variables are defined in Table 1. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A – Size-adjusted returns and transaction costs (all numbers are in %)

UR Decile	*AbRet3*	*AbRet12*	*Commission*	*ESpread*	*QSpread*	*LDV*
1	-1.49	-1.26	2.04	5.93	7.85	7.73
2	-0.82	1.55	1.43	4.17	5.66	5.50
3	-0.36	-0.42	1.21	3.40	4.60	4.52
4	-0.08	0.49	1.02	2.82	3.82	3.77
5	0.03	1.44	0.93	2.57	3.52	3.47
6	0.25	2.61	0.91	2.61	3.58	3.59
7	0.62	3.17	0.92	2.71	3.73	3.84
8	1.20	4.27	0.98	2.93	4.02	4.23
9	1.61	4.05	1.06	3.23	4.42	4.81
10	2.50	5.33	1.27	3.85	5.20	6.00
All	0.32	2.12	1.23	3.40	4.58	4.57

Panel B – Profitability analyses for trading strategy based on *UR*

UR Decile	*AbRet12*	*EProfit*	*QProfit*	*LDVProfit*
Short 1	-1.26	-4.67	-6.59	-6.47
Buy 10	5.33	1.47	0.13	-0.67
Hedge	6.59***	-3.19*	-6.46***	-7.14***
t-stat	4.03	-1.95	-3.96	-4.18

Panel C – 12-month abnormal returns (*AbRet12*) for *UE* and *UR* quintile portfolios

	UR Quintile				
UE Quintile	1	2	3	4	5
1	-2.99**	-3.51*	-1.41	-2.34**	-3.52**
2	-0.51	-2.05**	0.01	0.14	-0.05
3	1.16	-0.05	0.86	2.25**	1.48
4	4.73***	5.11***	4.62***	5.04***	5.40***
5	4.75***	4.52**	6.91***	9.91***	9.40***

Table 8 – cont'd

Panel D – Transaction costs in the extreme *UE* and *UR* quintiles

	UR Quintile					
UE Quintile	1	5	1	5	1	5
	ESpread		*QSpread*		*LDV*	
1	5.67	4.95	7.55	6.67	7.30	6.80
5	6.29	3.88	8.22	5.19	9.08	6.50
55-11 Return	12.92***		12.92***		12.92***	
55-11 Profit	1.73		-1.88		-2.55	

Table 9 – Profitability Analyses of PEAD Trading Strategy Using Analyst Expectation as Earnings Benchmark

Panel A (panel B) presents the profitability analysis of the PEAD trading strategy using equal-weighted (value-weighted) returns and transaction costs. The sample size is 213,022 firm-quarter earnings announcements from NYSE, AMEX, and NASDAQ from 1988 to 2005. The earnings surprises portfolios are formed using *Analyst UE*. *Analyst UE* is the difference between I/B/E/S EPS and I/B/E/S consensus analyst median EPS forecast scaled by price at the end of the fiscal quarter. All other variables are defined in Table 3. *, **, and *** indicate two-tailed statistical significance at 10, 5, and 1 percent levels.

Panel A – Equal-weighted profitability

	Three-month holding period				Twelve-month holding period			
	AbRet3	*EProfit3*	*QProfit3*	*LDVProfit3*	*AbRet12*	*EProfit12*	*QProfit12*	*LDVProfit12*
Short 1	-2.36	-2.27	-3.90	-3.66	-1.58	-3.05	-4.68	-4.44
Buy 10	3.97	0.67	-0.48	-0.91	12.12	8.82	7.67	7.24
Hedge	6.33***	-1.60***	-4.38***	-4.57***	13.70***	5.76***	2.99***	2.80***
t-stat	16.51	-3.63	-9.89	-9.72	12.96	5.32	2.75	2.69

Panel B – Value-weighted profitability

	Three-month holding period				Twelve-month holding period			
	AbRet3	*EProfit3*	*QProfit3*	*LDVProfit3*	*AbRet12*	*EProfit12*	*QProfit12*	*LDVProfit12*
Short 1	-1.28	-0.57	-1.46	-1.48	-0.70	-1.14	-2.03	-2.05
Buy 10	1.38	0.20	-0.39	-0.54	6.05	4.87	4.27	4.13
Hedge	2.66***	-0.36	-1.85**	-2.02***	6.75***	3.73**	2.24	2.07
t-stat	3.72	-0.51	-2.57	-2.91	4.67	2.57	1.53	1.44

Figure 1 – Abnormal Returns and Transaction Costs by Year

This figure presents mean abnormal returns (*AbRet12*) and effective spreads plus commissions (*ESpread*) by calendar year for the PEAD trading strategy. The earnings surprises portfolios are formed using *Analyst UE*. *Analyst UE* is the difference between I/B/E/S EPS and I/B/E/S consensus analyst median EPS forecast, scaled by price at the end of the fiscal quarter. *AbRet12* is the 12-month size-adjusted returns from the month following the announcement month. *ESpread* is the average daily effective spread plus commissions in the announcement month.