# The Efficiency of Market Reactions to Earnings News*

**Bin Miao†**
**National University of Singapore**

**Gillian H. Yeo**
**Nanyang Technological University**

**Abstract**

We examine the market reactions to earnings news with a stochastic frontier model approach. The model allows for the existence and estimation of the magnitude of inefficiency in the earnings-return relation. We find that the market's response to earnings news is more efficient for stocks that have larger market capitalization, more analyst following, lower transaction cost, less information uncertainty, higher institutional ownership, higher liquidity, and lower arbitrage risk. In addition, we show that our estimate of under-reaction is superior to standardized unexpected earnings (SUE) in predicting post-earnings announcement returns.

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† Corresponding author.
Email: miaobin@nus.edu.sg
Tel: (65) 6516-3083
1 Business Link, NUS Business School, Singapore 117592

## 1. Introduction

The efficient market hypothesis (EMH), which maintains that market prices fully incorporate all information, is one of the most widely debated topics in the finance and accounting literatures. The EMH implies that future security prices should not be predictable conditional on the current information set. To date, however, empirical research has documented a large number of market anomalies that seem inconsistent with the EMH (see Fama 1998, Schwert 2003 for a review of this research), raising considerable doubt about the rationality of security prices and the efficiency of financial markets.

Amidst this debate, critiques of extant studies of market (in)efficiency are abundant. Aside from discussions related to data and methodology, a growing number of researchers have voiced concern about the research question itself. For example, at a 2001 roundtable discussion of capital market rationality, Kenneth French argued that the question of market efficiency should be framed as a continuum instead of as a yes/no dichotomy as in most current studies (Doukas et al. 2002). This view is based on the observation that due to various market imperfections, it is impossible for perfectly efficient markets as described by the EMH to exist in reality (Grossman and Stiglitz 1980). Therefore, rather than test *whether or not* the market is efficient, it may be more fruitful to investigate *the degree to which* a market is informationally efficient (Campbell et al. 1997, Lo 2007).

In this study we empirically investigate the cross-sectional variation in the degree of market efficiency and its determinants within the continuum framework, focusing on the context of corporate earnings announcements. We focus on earnings announcements for two reasons. First, prior research shows that the market does not fully incorporate the value-implications of earnings news in a manner consistent with the EMH (post- earnings announcement drift, hereafter PEAD). Second, the market under-reacts to earnings announcements, a feature that is of particular interest for our research methodology as we discuss presently (Bernard and Thomas 1990, Kothari 2001, among many others).

Our continuous market efficiency measure is based on a stochastic frontier model (Aigner, Lovell, and Schmidt 1977 and Meeusen and van den Broeck 1977), which assumes that inefficiency always exists in a production system and hence that the realized output will always be less than the theoretical maximum value represented by production functions.[1] In a capital market setting, the outcome is the price of the stock and the inputs to the production function include information and other firm characteristics. If the market is perfectly efficient, then share prices should adjust completely and instantaneously after an information event. However, due to market frictions (such as high transaction costs) or investors' behavioral biases, inefficiencies creep into prices and the market under-reacts to information[2] Thus, the price-information relation under inefficiency makes earnings announcements a very suitable information event to study using the stochastic frontier approach (see Section 3 for further details). Note that the stochastic frontier model can be estimated at the individual stock level or the portfolio level. We estimate it at the portfolio level, which reduces the noise generated by liquidity-based trading around individual earnings announcements (Lee 1992). This approach yields one efficiency measure for each portfolio.

[1] Stochastic frontier models have been used in prior literature to estimate the magnitude of IPO under-pricing (Hunt-McCool et al. 1997), agency costs (Habib and Ljungqvist 2005), and the operational efficiency of commercial banks (Kwan 2006, and many other studies).

[2] Under-reaction has been shown to be the dominant effect for earnings announcements and many other corporate announcements such as dividends, splits, etc. In certain scenarios inefficiency may also result from investors' over-reaction.

Using a sample that consists of 1,251 portfolios containing 110,881 quarterly earnings announcements from 1985 to 2005, in our first analysis we estimate the earnings-return stochastic frontier model separately for good and bad news sub-samples to allow for variation in parameter values between these two types of information events. We find that the mean (median) estimate of the efficiency of the market's reaction to earnings news is 50.5% (50.2%) for positive unexpected earnings, and slightly lower at 47.4% (45.3%) for negative unexpected earnings. This suggests that, during the two decades covered by our sample, on average investors have been able to recognize less than half of the entire price implication at the time the earnings news was first made public. These results imply that investors' initial under-reaction to earnings news predicts abnormal returns of as much as 11.2% in the post-announcement period, assuming that the temporary mis-pricing will finally be corrected in the long run.[3] In addition, we find the portfolio-specific market efficiency estimates display considerable variation, ranging from as low as 0.6% to as high as 98.8%, with a standard deviation of 26.6%.

Next, we investigate the determinants of the cross-sectional variation documented above. Using several factors whose potential impact on market efficiency has been highlighted by previous research, we find that efficiency is generally higher for firms that have larger market capitalization, more analyst following, lower transaction costs, higher liquidity, less information uncertainty, lower arbitrage risk, and lower book-to-market.

Finally, we document a strong and positive correlation between our estimates of under-reaction at the time of announcement and post-announcement abnormal return. Perhaps more interestingly, we find that this correlation largely subsumes the ability of

[3] It is interesting to note that our estimate of the magnitude of under-reaction is comparable to the results reported by many prior PEAD studies, which use post-announcement abnormal return to measure initial under-reaction.

unexpected earnings to predict future returns. This finding provides further support to the hypothesis that the PEAD is due to investors' initial under-reaction to earnings news. In addition, it also implies that our measure is a more accurate proxy for the magnitude of under-reaction than the *SUE* measure that has been widely used in literature.

Our study makes important contributions to the literature by developing a new measure of the degree of market efficiency under the continuum framework and providing direct estimates of the magnitude of investors' under-reaction to earnings announcements. Extant studies have mostly relied on the post-event abnormal return as an indirect proxy for the magnitude of initial under-reaction (e.g. Frazzini 2006, Vega 2006, and most other PEAD studies). However, this method is subject to several problems that could significantly reduce the accuracy of estimation.

First, the well-known expected return model specification problems cause estimated abnormal return to be biased, especially when they are cumulated over relatively long periods as in the PEAD studies. For example, Ball et al. (1988) find that betas tend to shift upwards after good earnings news and vice versa. Although the limited magnitude of beta shifts is not enough to entirely explain away the post-announcement drift (Bernard and Thomas 1989), it likely results in overstated abnormal returns.

Second, the market's initial under-reaction to earnings news may not always lead to post-announcement price drift, a phenomenon that occurs when the gap between a security's price and fundamental value is not large enough to cover the transaction costs required to profit from the mispricing. In this case, even if prices were set by irrational market participants at the time of an earnings announcement, the market remains Minimally Rational (Rubinstein 2001) and post-announcement drift will not be observed.

Therefore, PEAD may not always be a manifestation of the market's self correction process, and in some cases, ex post observed drift may not be related to investors' initial under-reaction to earnings news at all.

The last issue in using abnormal announcement returns to estimate the magnitude of initial under-reaction is that neither the timing nor the duration of PEAD can be easily determined. For instance, while theories tell us why PEAD could occur, they make few predictions about when the drift will occur and how long it will last.[4] Moreover, many behavioral finance models suggest return reversals in the long run. As a consequence of the absence of theoretical guidance, past studies of PEAD have used various announcement periods, ranging from 60 trading days to three years after earnings announcement. Not surprisingly, the reported magnitudes of drift have also been vastly diverse (Doyle et al. 2006).[5]

In contrast to the traditional approach, the method we use to estimate the magnitude of under-reaction does not require post-announcement market information. Instead, it uses only unexpected earnings and short-window (2-day) announcement returns as inputs. Our method is therefore free of the problems discussed above.

The rest of the paper proceeds as follows. Section 2 reviews the related literature and Section 3 introduces the methodology. Section 4 describes the sample and defines our variables. Results are discussed in Section 5. The last section, Section 6, concludes.

## 2. Literature review

### *2.1. Post-earnings announcement drift (PEAD)*

[4] It is also very likely that the length of PEAD will vary across announcement events.
[5] As expected, much variation in the strength of the estimated drift is caused by the different return-accumulation periods and risk adjustment methods employed.

Post-earnings announcement drift (PEAD) refers to the predictable pattern whereby, after the announcement of quarterly earnings, equity prices continue to move in the same direction of the earnings surprise for a prolonged period. Abnormal returns that can be earned based on a PEAD trading strategy have been shown to be significant both economically and statistically, with the bulk concentrating around subsequent earnings announcements (e.g., Foster et al. 1984, Bernard and Thomas 1989).

The PEAD phenomenon, which has survived through various robustness checks, has puzzled researchers since first observed in the seminal paper of Ball and Brown (1968).[6] Early research attempts to put PEAD in a rational market framework by suggesting that the observed drift may result from the mis-specified model for calculating abnormal returns (Ball 1978, Ball et al. 1988, and Foster et al. 1984). While undeniably a possibility, this explanation is less than satisfying because the persistence and magnitude of the drift are not likely to be entirely explained away by such research design imperfections (Kothari 2001). In contrast, empirical evidence appears to be consistent with the argument that PEAD results from the market's delayed reaction (under-reaction) to earnings news. Bernard and Thomas (1989) is among the first studies to provide evidence in line with this argument. In particular, they show that naïve investors do not understand the true time-series process of quarterly earnings, and thus fail to fully appreciate the ability of current earnings news to predict future earnings. As a result, the market continues to be surprised by ensuing earnings that are partially predictable, and hence abnormal returns recorded around subsequent short-window earnings announcements constitute the bulk (as much as 40% for small firms) of total abnormal returns from a PEAD strategy. More recent studies, including Ball and Bartov (1996), Burgstahler et al. (1999), and

[6] Please see Kothari (2001) for an extensive survey of the PEAD literature.

Soffer and Lys (1999), generally report results that confirm this under-reaction proposition, although some disagreement exists regarding the degree of investor naivety.[7]

Given the empirical evidence of PEAD mostly points to investors' inefficient use of public information, an even more fundamental question that arises is why this market anomaly, an apparent violation of the market efficiency hypothesis, has not been arbitraged away. Extant literature offers several possible answers to this question. One view, mostly held by behavioral finance researchers, argues that investors' persistent under-reaction to earnings news results from heuristic cognitive biases, such as conservatism (Barberis et al. 1998), overconfidence and the self-attrition bias (Daniel et al. 1998), the disposition effect (Frazzini 2006), etc. For example, the disposition effect of Shefrin and Statman (1985) predicts that at earnings announcements, investors tend to sell prematurely on good news to realize gains, but hold on bad news because of their reluctance to realize losses.[8] Hence, the tendency for investors to hold losers too long and sell winners too soon suggests they always under-react to earnings news (Grinblatt and Han 2005). Empirical evidence on the impact of the disposition effect on PEAD is provided by a recent study by Frazzini (2006), who finds that his measure of the disposition effect for mutual fund managers, which is calculated from the temporal changes of mutual fund holdings for a particular stock, helps explain the cross-sectional variation of post-earnings announcement drift.

Another view, which does not assume market irrationality, maintains that the under-reaction is caused by transaction costs that prevent arbitrageurs from exploiting the

[7] For example, Ball and Bartov (1996) suggest that investors are not entirely naïve in understanding the autocorrelations of quarterly earnings, but rather they tend to underestimate the parameters of the autoregressive process, whereas Soffer and Lys (1999) dispute this argument by showing that investors' expectations, as reflected by stock prices, do not capture any predictive power of past earnings.

[8] The theoretical foundation of the disposition effect is laid by the interaction of the "prospect theory" of Kahneman and Tversky (1979) and the "mental accounting" framework of Thaler (1980). Please see Grinblatt and Han (2005) for an excellent delineation of how prospect theory, together with mental accounting, explains the disposition effect.

temporary mispricing. This explanation was first examined by Bernard and Thomas (1989), who find an upper bound on the drift that is unrelated to the magnitude of earnings surprises, consistent with the prediction of the transaction cost argument. Another piece of evidence is provided by Bhushan (1994), who use price and volume as proxies for trading cost and find that the magnitude of PEAD is positively related to these trading cost measures. As a result of the availability of high frequency trading data and advances in market microstructure research, this transaction cost explanation has gained new support from recent studies that use finer estimates of trading costs calculated directly from intra-day trading data. For example, both Ng et al. (2007) and Chordia et al. (2007) report evidence that the "paper gains" from the PEAD trading strategy are significantly reduced when the trading costs incurred by implementing this strategy are taken into account.

### *2.2. Stochastic frontier model*

In this study, we develop a measure of the degree of market efficiency by exploiting the empirical regularity of market under-reaction at earnings announcements.[9] Our estimation technique is based on the stochastic frontier model.

The stochastic frontier model, introduced simultaneously by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), has been widely applied in industrial productivity analyses. The concept of frontier arises from the fact that inefficiency normally exists in any production process, and therefore realized output will always be less than the theoretical maximum value represented by production functions. The standard formulation of a stochastic frontier model is

[9] It is important to note that our methodology is neutral with respect to the alternative theories behind the under-reaction.

$$y_i = f(x_i, \beta) + \varepsilon_i \,, \tag{1}$$

where $y_i$ is output, $\boldsymbol{x_i}$ is a vector of inputs, $\boldsymbol{\beta}$ is a vector of parameters, and $\varepsilon_i$ is the error term for observation *i.* The feature that distinguishes the stochastic frontier model from the traditional production model is that its error term $\varepsilon_i$ is composed of two independent parts,

$$\varepsilon_i = v_i - u_i \,. \tag{2}$$

The first component, $v_i$, is a normally distributed ( $v_i \sim N(0, \sigma_v^2)$ ) error term that represents the usual statistical noise in any regression, and the second component, $u_i >= 0$ , is a one-sided error term with half-normal distribution $u_i \sim N^+(0, \sigma_u^2)$ [10] that captures the production inefficiency.[11] Both of the error terms are independent of each other and of all the input variables.

For the purpose of our study, the most appealing feature of the stochastic frontier model lies in the fact that it not only allows for the existence of inefficiency, but also provides estimates of the magnitude of inefficiency. In capital market settings, and for earnings announcement events in particular, the input to the production system is the company's earnings news, and the output is changes in its share price. In a perfectly efficient market, share price adjustments should be complete immediately after the announcement and the new price should be at the level suggested by the valuation model. Inefficiency in the capitalization process will cause under-reaction to earnings news, resulting in share prices below or above the optimal level depending on the nature of the news. Therefore, the stochastic frontier approach could be a very useful tool for the

[10] $u_i$ is distributed as the absolute value of a $N(0, \sigma_u^2)$ variable.

[11] Econometricians have proposed other distribution functions for the one-sided error term, such as exponential, gamma, and truncated normal. In this study we consider only the half-normal case because it is used most often. Also, there is evidence showing that the estimation results are not very sensitive to the distribution assumption adopted (see Greene 1990, for example).

purpose of modeling the earnings-return relation under inefficiency and estimating the magnitude of the inefficiency in the market's reaction to earnings news.

Our study is not the first to apply the stochastic frontier model in capital market research. Indeed, there are many interesting applications of the model in accounting and finance. For example, Hunt-McCool et al. (1997) use it to estimate the magnitude of IPO under-pricing. Dupoch and Gupta (1997) apply the model in a managerial accounting setting to estimate the benchmark standard for relative performance evaluation. Habib and Ljungqvist (2005) develop a method from the stochastic frontier model to directly estimate the magnitude of agency costs in public companies. In addition to the studies surveyed above, researchers have also used the model to study the operating efficiency of commercial banks (e.g., Kwan 2006, among many others).

## 3. Methodology

We use a power function to model the relation between unexpected earnings and abnormal return:

$$|AR_{i,t}| = \alpha \cdot |SUE_{i,t}|^{\beta} \cdot ME_{i,t} \cdot \Omega_{i,t}. \tag{3}$$

In equation (3), $|AR_{i,t}|$ denotes the absolute value of stock *i*'s abnormal return around the announcement, $|SUE_{i,t}|$ denotes the absolute value of standardized unexpected earnings,[12] $ME_{i,t} \in (0,1]$ measures the efficiency of the market's reaction to the earnings news, taking the value of one when the market is perfectly efficient, $\Omega_{i,t} > 0$ is the random shock to the function, and $\alpha$ and $\beta$ are parameters describing the function. We choose the power function over the more commonly used linear function because empirical

[12] We use the absolute value to make sure the model is meaningful for negative *AR* and *SUE* values.

evidence shows that *AR* and *SUE* are not linearly related. Instead, they have an S-shape relation, meaning that more extreme earnings news tends to result in less price movement on a per *SUE* basis (see Freeman and Tse 1993 and Kinney et al. 2002, among others).[13]

Equation (3) can be estimated using traditional linear regression methods after being logarithmically transformed, that is,

$$\ln|AR_{i,t}| = \ln\alpha + \beta\cdot\ln|SUE_{i,t}| + \ln ME_{i,t} + \ln\Omega_{i,t} \tag{4}$$

or

$$ar_{i,t} = a + \beta\cdot sue_{i,t} - u_{i,t} + v_{i,t}\,, \tag{5}$$

where $ar_{i,t} = \ln|AR_{i,t}|$ , $a = \ln\alpha$ , $sue_{i,t} = \ln|SUE_{i,t}|$ , $u_{i,t} = -\ln ME_{i,t}$ , and $v_{i,t} = \ln\Omega_{i,t}$. Since by definition $ME_{i,t} \in (0,1]$ and $\Omega_{i,t} > 0$, we have $u_{i,t} \in [0,+\infty)$ and $v_{i,t} \in (-\infty,+\infty)$ . We further assume that $u_{i,t}$ follows a half-normal distribution of $u_i \sim N^+(0,\sigma_u^2)$ , $v_{i,t}$ is normally distributed as $v_i \sim N(0,\sigma_v^2)$ , and $sue_{i,t}$, $u_{i,t}$, and $v_{i,t}$ are mutually independent of each other.

It is important to note that, while equation (5) models market inefficiency as investors' under-reaction to earnings news, it accommodates instances of over-reaction as well. In particular, given that under-reaction plays the dominant role in investors' response to earnings news,[14] we treat under-reaction as the systematic effect and over-reaction as the random effect in the stochastic frontier model. As such, over-reactions, possibly due to exogenous factors such as upbeat or downbeat market sentiments, occasionally enter into the earnings-return relationship as random shocks, and hence will be captured by the symmetrically distributed error term $v_{i,t}$. In these cases, over-reaction will result in positive

[13] In equation (3), the relation between *AR* and *SUE* would display an S-shape if $0<\beta<1$. Hence, our empirical estimate of $\beta$ provides a check on whether our model is mis-specified.
[14] This is suggested by prior literature. In addition, the empirical test discussed in Section 5.1 also supports this assumption.

realizations of $v_{i,t}$, and as a consequence we may observe that the output value (*ar*) lies above the deterministic part of equation (5), $\alpha + \beta \cdot sue$. Therefore, due to its muted impact on estimates of parameters $\alpha$ and $\beta$, the presence of observations with over-reaction will not necessarily force the estimated efficient frontier artificially high and cause all estimates of market efficiency to be downwardly biased. In addition, as we will discuss in Section 4, we use portfolios instead of individual earnings announcements to implement the estimation. This approach should greatly reduce the chance of occurrence of over-reactions in our data.

Let $\varepsilon_{i,t}$ denotes the "composed error" for equation (5), with $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$. It can be shown that the probability density function of $\varepsilon_{i,t}$ is

$$f(\varepsilon) = \tfrac{2}{\sigma} \cdot \phi(\tfrac{\varepsilon}{\sigma}) \cdot \Phi(-\tfrac{\varepsilon\lambda}{\sigma}), \tag{6}$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, $\lambda = \sigma_u / \sigma_v$, and $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal cumulative distribution and density functions, respectively (subscripts omitted for brevity).[15] The new parameters σ and λ are used because of the convenience they provide in evaluating the relative contributions of *u* and *v* to *ε*. As $\lambda \to 0$, either $\sigma_u \to 0$ or $\sigma_v \to \infty$, and the one-sided error term is dominated by the two-sided error term. In this extreme case, there is no inefficiency in the capitalization process and equation (5) collapses to an OLS regression.

Since the distribution of the error term is assumed to be known, parameters of equation (5), including *α, β, λ*, and *σ*, can be estimated simultaneously by maximum likelihood methods. The log-likelihood function is

[15] Please see Kumbhakar and Lovell (2000) p. 75 for a derivation of the density function of the "composed" error *ε*.

$$\ln L = C - N\ln\sigma + \sum_{i,t}\ln\Phi(-\tfrac{\varepsilon_{i,t}\cdot\lambda}{\sigma}) - \tfrac{1}{2\sigma^2}\sum_{i,t}\varepsilon_{i,t}^2 \,, \tag{7}$$

where $C$ is a constant and $N$ is the number of observations.

Using the approach proposed by Lee and Tyler (1978), we obtain the estimator for the average efficiency of all earnings announcement observations as follows:

$$E(ME_{i,t}) = E(\exp(-u_{i,t})) = 2[1-\Phi(\sigma_u)]\cdot\exp(\sigma_u^2/2)\,. \tag{8}$$

Equation (8) gives only the average level of the efficiency of the market's reaction to earnings news, and intuitively one would want to know the efficiency for each earnings announcement event. Jondrow et al. (1982) suggests that since $\varepsilon_{i,t}$ contains information about $u_{i,t}$, we can use the conditional distribution of $u_{i,t}$ given $\varepsilon_{i,t}$ to draw an inference about $u_{i,t}$. Further, they show that a point estimator for $u_{i,t}$ is given by the conditional expectation of $u_{i,t}$ given $\varepsilon_{i,t}$:[16]

$$E(u_{i,t} \mid \varepsilon_{i,t}) = \frac{\sigma_u^2\sigma_v^2}{\sigma^2}\left[\frac{\phi(\varepsilon_{i,t}\lambda/\sigma)}{1-\Phi(\varepsilon_{i,t}\lambda/\sigma)} - \left(\frac{\varepsilon_{i,t}\lambda}{\sigma}\right)\right]. \tag{9}$$

Battese and Coelli (1988) make an important extension to Jondrow et al.'s (1988) result by showing that the conditional expectation of $ME_{i,t} = \exp(-u_{i,t})$ is given by

$$E[ME_{i,t} \mid \varepsilon_{i,t}] = \left\{\frac{1-\Phi[\sigma_* - (\mu_{i,t}^*/\sigma_*)]}{1-\Phi(-\mu_{i,t}^*/\sigma_*)}\right\}\cdot\exp(-\mu_{i,t}^* + \tfrac{1}{2}\sigma_*^2)\,, \tag{10}$$

where $\mu_{i,t}^* = -\varepsilon_{i,t}\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_v^2\sigma_u^2/\sigma^2$.

So far we have a point estimate for the efficiency of the market's reaction to earnings news at the observation level, $\hat{ME}_{i,t} = E[ME_{i,t} \mid \varepsilon_{i,t}]$. We conclude this section

[16] Please see the Appendix of Jondrow et al. (1982) for a mathematical derivation of this result.

by translating efficiency into under-reaction. Rearranging terms in equation (3), it can be shown that our estimate for the magnitude of the market's under-reaction to earnings news is given by

$$UR_{i,t} = \left(\frac{1}{ME_{i,t}} - 1\right) \cdot AR_{i,t} \quad . \tag{11}$$

## 4. Variable construction and sample selection

In order to investigate the market's reaction to an earnings surprise, we first need to know how much of the disclosed earnings is anticipated and has been reflected in prices before the announcement. However, accurate measurement of expected earnings is difficult.[17] Past PEAD studies have relied on time-series models of quarterly earnings (e.g., Bernard and Thomas 1989, Collins and Hribar 2000) or sell-side analyst forecasts (e.g., Affleck-Graves and Mendenhall 1992, Liang 2003) to proxy for earnings expectations. Although both methods are subject to measurement error (Maddala and Nimalendran 1995, Lo and Lys 2001), the latter measure is generally believed to be superior to the former because analysts incorporate more timely information in their estimates and thus tend to outperform time-series models in terms of forecast accuracy (Brown and Rozeff 1978). Moreover, in a recent study, Livnat and Mendenhall (2006) show that post-earnings announcement drift is significantly larger when unexpected earnings are defined as analyst forecast error than when defined as prediction error from a seasonal random walk model,

[17] Evidence from trading volumes at earnings announcement suggests that market participants hold heterogeneous beliefs about firm value prior to the announcements. Therefore, the use of any single earnings expectation proxy for the entire market will likely result in measurement error (Utama and Cready 1997, Bhattacharya 2001, Battalio and Mendenhall 2005).

suggesting the former is more closely correlated with the unobservable factors that lead to PEAD.

Based on the above discussion, we define the standardized unexpected earnings as

$$SUE_{i,t} = \frac{E_{i,t} - F_{i,t}}{P_{i,t}}, \tag{12}$$

where $E_{i,t}$ is actual quarterly earnings on the I/B/E/S summary file, $F_{i,t}$ is the mean forecast of quarterly earnings on the I/B/E/S summary file,[18] and $P_{i,t}$ is the closing price two days before the earnings announcement date. We use actual earnings from I/B/E/S rather than COMPUSTAT because I/B/E/S excludes certain non-recurring special items to ensure the actual earnings are defined in line with forecasted earnings, and hence forecast errors calculated in this way better mimic the true "surprise" to investors (Bradshaw and Sloan 2002, Collins et al. 2005). Abnormal returns at earnings announcement are calculated as the raw return less the return on the size-decile portfolio in which the firm is member. A three-day window around the earnings announcement date is used to compound the daily returns. We include one day before the earnings announcement to control for information leakage, and one day after the announcement to accommodate announcements made after market close.[19]

To construct our sample, we begin with all quarterly earnings announcements from 1985 to 2005 that satisfy the following screening criteria:

[18] The mean forecast on the I/B/E/S summary file may contain forecasts that are no longer current. However, Diether et al. (2002) and Vega (2006) find this issue is only a minor concern that has no impact on their results.

[19] COMPUSTAT and I/B/E/S only record the date, not the time, of earnings announcements, so it is unknown whether an announcement is made before market open, during market hours, or after market close.

1) The mean estimates and actual quarterly earnings data must not be missing on the I/B/E/S summary file. In addition, we require at least two earnings estimates in the calculation of mean estimates.[20]

2) All necessary return and price data are available from CRSP. Also, we use only stocks with CRSP share code 10 or 11, thus excluding Real Estate Investment Trusts, close-end funds, American Depository Receipts, and non-U.S. incorporated companies.

3) Since both forecast and actual earnings are from I/B/E/S, we also use the report date on the I/B/E/S summary file as the earnings announcement date to maintain consistency. However, we use the date on the COMPUSTAT quarterly file to ensure the accuracy of the earnings announcement date on I/B/E/S. We require that the difference between the two dates not exceed one day.

4) To exclude outliers, we truncate the sample to restrict the distribution of *SUE* to be between -1 and 1.

At the individual stock level, price movements at earnings announcements can be highly volatile and measurement error of unexpected earnings can be substantial. These problems may introduce large statistical noise in the regression model and affect the precision of parameter estimates. At the portfolio level, however, these problems should be significantly mitigated by the cancelling-out of noise. Therefore, the earnings-return relation estimated at the portfolio level should be more stable and the inferences drawn should have higher accuracy. Consistent with this observation, most prior studies of the

[20] In addition to calculation of *SUE*, this requirement is also necessary to calculate the standard deviation of forecasts, which is among the possible determinants of market efficiency that we examine in Section 5.2. However, we acknowledge that this data restriction may introduce a selection bias to our sample, as firms covered by I/B/E/S may differ from those without analyst following in certain dimensions, such as size. This potential selection bias may affect the generalizability of our results to firms with no analyst coverage.

PEAD effect use *SUE* portfolios and thus the documented evidence on market under-reaction is also at the portfolio level instead of the individual stock level.

Following this literature, for each calendar month we rank all the stocks that announce earnings in that month into ten decile portfolios based on *SUE*. This procedure results in 2,520 portfolios. We observe that the number of stocks in each portfolio varies greatly, reflecting the uneven temporal distribution of earnings announcements. For example, as shown in Figure 1, earnings announcements demonstrate a clear seasonal pattern, with the great majority clustering in January, April, July, and October. This is consistent with most companies choosing December as their fiscal year-end. To ensure that all portfolios are well diversified, we drop those containing less than 30 stocks.

<Please insert Figure 1 here>

Next, we treat each portfolio as one single earnings announcement observation and assign the equal-weighted average *SUE* and *AR* of all stocks in the portfolio as the *SUE* and *AR* for that portfolio, respectively:

$$AR_{j,t} = \frac{1}{n} \times \sum_{i=1}^{n} AR_{i,t} \qquad SUE_{j,t} = \frac{1}{n} \times \sum_{i=1}^{n} SUE_{i,t} \ , \tag{13}$$

where we use *i* to index stocks and *j* to index portfolios. We then minimize potential measurement error of earnings surprises by restricting the sign of portfolio *AR* to be consistent with that of *SUE*, i.e.,

$$AR_{j,t} \cdot SUE_{j,t} > 0 \ . \tag{14}$$

Note that there is another reason to impose the requirement in (14). Recall that we need to make logarithmic transformations of the absolute value of *AR* and *SUE* for estimation of equation (3). Absent the restriction of equation (14), incorrect inferences may be drawn because in equation (4) the original signs of *AR* and *SUE* are no longer identifiable.[21]

The final sample consists of 1,251 portfolios representing 110,881 quarterly earnings announcements from 1985 to 2005.

## 5. Results

### *5.1 Estimation of market efficiency and under-reaction*

Researchers find that the market reacts differently to a positive versus negative earnings surprise, probably due to the lower persistence of negative earnings surprises (Abarbanell and Lehavy 2004). Consistent with these findings, we allow for different parameters between good news and bad news announcements by estimating equation (5) separately for good and bad news sub-samples.[22]

Panel A of Table 1 presents the summary statistics of *SUE* and *AR* for the 689 good news portfolios and 562 bad news portfolios. The OLS estimation results of equation (5) are given in Panel B of Table 1. The parameter estimates are significantly different between the two sub-samples. In particular, equation (5) performs much better for the good news sub-sample than the bad news sub-sample, as evidenced by the $R^2$s (28.5% vs. 18.3%). Thus, separate investigation of these two groups of firms seems warranted. It is also worth noting that the explanatory power of the earnings-return model (equation (5)) is substantially improved when estimated at the portfolio level relative to the stock level,

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[21] We acknowledge that this additional restriction may exclude some extreme cases of under-reaction, i.e., negative (positive) price reactions to positive (negative) earnings news. However, we believe this concern is attenuated because for these cases it is more likely that the price is reacting to information other than earnings, such as revenue (Ghosh et al. 2005, Ertimur et al. 2003).
[22] The good news sub-sample includes all observations with SUE>0, while the bad news sub-sample includes all observations with SUE<0.

suggesting that our sorting is successful in increasing the signal-to-noise ratio of the model's variables (*SUE* and *AR*).[23]

Although the parameters that capture inefficiency ($u$ in equation (5)) cannot be estimated by the method of ordinary least squares (OLS), OLS provides a simple test for the presence of inefficiency. Recall that in equation (5) the "composed" error term is $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$. If $u_{i,t} = 0$, i.e., if there is no inefficiency, then $\varepsilon_{i,t} = v_{i,t}$ and is symmetrically distributed. Alternatively, if $u_{i,t} > 0$, then $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$ is negatively skewed and the under-reaction story is supported. Therefore, examining the skewness of OLS residuals provides a simple test of the existence of inefficiency in our earnings announcement data (Schmidt and Lin 1984).

Panel C of Table 1 presents the statistics of OLS regression residuals for equation (5). It can be seen from the fourth column that the skewness statistics are negative for both good and bad news sub-samples. The last columns show the test statistics against the null hypothesis that the residuals are normally distributed.[24] Again, the normality assumption is rejected by the data at high significance levels for each of the regressions. Therefore, preliminary evidence from the data is supportive of the presence of inefficiency in the market's reaction to earnings news.[25]

<Please insert Table 1 here>

[23] We conduct bootstrap analysis by randomly sampling individual stocks and run the earnings-return regression. We keep the sample size equal to 689 for the good news sample and 562 for the bad news sample to be consistent with the portfolio regressions. We repeat the sampling 1,000 times and record the empirical distribution of the $R^2$. The results (unreported) show that the average value of the stock-level $R^2$ is far lower than the portfolio-level $R^2$ reported in Table 2.

[24] Normality test statistics: when the sample size is less than or equal to 2,000, the Shapiro-Wilk test statistic is used; when the sample size exceeds 2,000, the Kolmogorov D Statistic is used.

[25] There is a caveat in interpreting the skewness test result. Log-transformed returns are generally negatively skewed. Since the regression residual is related to the dependent variable, the negative skewness of the residual may also be caused by the negatively skewed dependent variable (log-return).

Panel A of Table 2 presents maximum likelihood (ML) estimates of the parameters in equation (7), the log-likelihood function. The OLS estimates of $\alpha$ and $\beta$ are also replicated in the last two rows for ease of comparison.

We can see from Panel A that the OLS estimates of $\alpha$ are smaller than the ML estimates, while the $\beta$'s estimated by the two methods are very close to each other. This result is not unexpected. Since we assume in equation (5) that $u_{i,t}$ and $v_{i,t}$ are independent of the regressor $SUE_{i,t}$, OLS will produce unbiased and consistent estimates for $\beta$. In contrast, because the expectation of the error term is $E[\varepsilon_{i,t}] = -E[u_{i,t}] <= 0$, the OLS estimate for the intercept $\alpha$ will be negatively biased (Kumbhakar and Lovell 2000, Greene 2003). Therefore, the comparison of the OLS and ML estimates of $\alpha$ and $\beta$ supports our prediction that inefficiency is present in the earnings-return relation.

Panel A also shows that the point estimates of $\beta$, which is the slope parameter in equation (5) and the power parameter in equation (3), have values between zero and one in both of the regressions. This implies that, neglecting the random error terms $ME_{i,t}$ and $\Omega_{i,t}$, the earnings-return function in equation (3) has a positive first derivative and negative second derivative.[26] Thus, our model describes a declining marginal market response as the magnitude of absolute earnings surprises increases, which is consistent with the empirical finding of an S-shape earnings-return relation (Freeman and Tse 1992, Kinney et al. 2002).

A third result from Panel A of Table 2 is that the point estimates of $\lambda = \sigma_u / \sigma_v$, which measures the relative contribution to total variance of the residual from $u_{i,t}$ and $v_{i,t}$, are greater than one for both good news and bad news observations. This suggests the one-

[26] Recall that absolute values of *SUE* and *AR* are used in equation (3).

sided error component $u_{i,t}$ dominates the symmetric error term $v_{i,t}$ in the composition of $\varepsilon_{i,t}$, and hence the magnitude of inefficiency may be rather large. The eighth row shows the estimates of the mean level of market efficiency using the method proposed by Lee and Tyler (1978) (Equation (8)). On average, the efficiency of the market reaction to earnings surprises has been around 46.8% for good news announcements, and slightly lower at around 45% for bad news announcements. In other words, price movements at earnings announcements have been able to recognize less than half of the full value implications of the earnings news.

Panel B of Table 2 gives the statistics of portfolio-specific estimates of market efficiency calculated by equation (10), the approximation method proposed by Battese and Coelli (1988). We can see that the portfolio-specific $ME_{i,t}$ estimates average around 50.5% for good news observations, and 47.4% for bad news observations. These values, while slightly higher, are generally in line with the estimates calculated by equation (8) and reported in Panel A. The efficiency levels also display considerable cross-sectional variation. In particular, the efficiency estimates range from as low as 0.6%, suggesting that in some extreme cases investors totally ignore the value-relevance of earnings news, to as high as 98.8%, suggesting that nearly all of the implications of earnings news is reflected in prices by the end of the announcement.

Panel C of Table 2 reports estimates of the magnitude of under-reaction as calculated by equation (11). The market's under-reaction to unexpected earnings, measured in terms of returns that fail to materialize, is on average 1.8% for positive earnings news portfolios and -1.8% for negative earnings news portfolios. Results from the two extreme portfolios, which have under-reactions of 6.3% to good news and -4.9% to bad news, predict future abnormal returns of 11.2% from the hedged portfolio, assuming the market will finally correct any temporary mis-pricing in the long run.[27]

<Please insert Table 2 >

*5.2. Determinants of market efficiency*

In Table 2 we find considerable variation in our *ME* estimates across earnings announcement portfolios. In this section we investigate the determinants of this cross-sectional variation. In particular, we examine the following list of variables, all of which have been suggested by prior research to affect the informational efficiency of market prices.

*Market Value of Equity (MV)*: Firm size is an important variable that has been frequently used in studies of market efficiency, because, among other reasons, size is directly correlated with many factors that contribute to pricing efficiency, such as information environment, liquidity, etc. Most documented market anomalies, including the post-earnings announcement drift, have been found to be confined to or more pronounced for small firms (Fama 1998). Therefore, we include firm size and expect it to have a positive impact on the degree of market efficiency. The variable *MV* for each firm is measured as of the beginning of the calendar month during which the earnings announcement is made. *MV* for the portfolio is calculated as the average *MV* for all the stocks in the portfolio.

*Analyst Following (NUMEST)*: Past research suggests that financial analysts serve as effective information intermediaries and facilitate pricing of accounting and other value-

[27] It is important to note, however, that this does not necessarily represent the profits that can be earned from a practically implementable investment strategy.

relevant information (e.g., Barth and Hutton 2004). We include analyst coverage as a proxy for the firm's information environment and expect it to be positively related to our measure of market efficiency. The empirical proxy for analyst coverage is the number of earnings estimates that are included in calculating the consensus forecast in the I/B/E/S summary file. The portfolio-level *NUMEST* is the average value for all stocks in the portfolio.

*Institutional Ownership (INST)*: Institutional ownership has been used in prior literature as a proxy for investor sophistication (Hand 1990, Walther 1997, Collins et al. 2003). Bartov et al. (2000) find that post-earnings announcement abnormal returns are significantly smaller for firms with high institutional ownership, suggesting the pricing efficiency of earnings news is improved by investor sophistication. Therefore, we expect this variable to be positively correlated with our market efficiency estimates. We use data from companies' 13F filings archived by Thompson Financial to calculate the proportion of shares held by institutional investors as of the beginning of the month of earnings announcements. The averages of stock-level data are used to generate portfolio measures.

*Transaction Cost (DVOL, PRC)*: For thinly traded stocks, high transaction costs may impede the price discovery process, resulting in biased valuations. Consistent with this argument, Bhushan (1994) finds that PEAD is stronger for stocks that are more costly to trade. We use two variables to measure transaction cost: the share price at the beginning of the month of the earnings announcement (PRC) and the average dollar trading volume over the twelve months prior to the month of the earnings announcement (DVOL).[28] Both

[28] Dollar trading volume for each month is calculated as the month's share volume multiplied by closing price. For stocks listed on NASDAQ, we multiply the reported volume by 0.5 to adjust for the bias in the calculation of volume (Anderson and Dyl 2005). Our results are similar without this adjustment.

of these variables are expected to have a positive impact on market efficiency, and as above, the average of the stock-level values is used for the portfolio value.

*Illiquidity (ILLIQ)*: Chordia et al. (2007) conduct a careful analysis of the impact of trading costs on the profitability of a PEAD trading strategy. They find that the PEAD effect is prevalent mainly in stocks that are relatively illiquid to trade, suggesting that one important reason for investors' delayed reaction to earnings announcements is trading costs. We follow Chordia et al. (2007) and use the liquidity measure proposed by Amihud (2002) as an additional variable to gauge the difficulty of trading:

$$ILLIQ = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6 \tag{15}$$

In equation (15), $D_{it}$ is the number of trading days, $R_{itd}$ is the daily return, and $DVOL_{itd}$ is the daily dollar volume.[29] This measure is based on the idea that the more liquid the stock, the smaller impact each trade should have on price. The variable measures the average daily price impact of order flow and is expected to be negatively correlated with market efficiency. It is calculated for each stock using daily return and volume data over the year before the month of the earnings announcements.[30] The average of stock-level estimates is then used for the portfolio estimate.

*Information Uncertainty (STDEV)*: A common assumption shared by most behavioral models of investors' under-reaction to earnings news is that the earnings news itself is only a noisy signal about liquidating firm value. In other words, psychological biases work against efficient pricing of earnings news only if uncertainty about the news' informativeness exists. Recent studies find that short-term price continuation grows

[29] The volumes for NASDAQ-listed stocks are multiplied by 0.5 to adjust for reporting bias. See footnote 27.
[30] We require at least 20 non-missing daily data to calculate the variable.

stronger as information uncertainty increases (Zhang 2006). Therefore, we expect market efficiency to be negatively affected by information uncertainty. We use the opinion dispersion of financial analysts, who constitute an important subset of all market participants, to measure information uncertainty. The variable *STDEV* is the standard deviation of all earnings estimates that are used in calculating the consensus forecast in the I/B/E/S summary file. To control for the scale difference across firms, we first divide the *STDEV* for each firm by its share price and then average the price-deflated stock-level values to get the portfolio-level variable.

*Arbitrage Risk (ARBRISK)*: Under textbook market efficiency hypotheses, any arbitrage opportunity that results from mis-pricing will be exploited by rational traders whose trading will (instantaneously) push security prices back to equilibrium levels commensurate with fundamental value. In the real world, however, arbitrageurs are subject to many constraints, such as capital inadequacy, transaction costs, and holding costs, and these constraints are likely to keep prices from fully converging toward intrinsic value (Shleifer and Vishny 1997, Pontiff 2006). An important limit of arbitrage is represented by the idiosyncratic risk faced by arbitragers. Idiosyncratic risk makes arbitrage risky because these risks are security-specific and thus cannot be effectively hedged by establishing contrary positions in the common risk factors. Pontiff (2006) uses a simple model to show that the incentive of arbitrageurs to exploit mis-pricing decreases with the idiosyncratic volatility of the security in question. Empirical evidence also shows that market anomalies are more likely to be found for stocks with higher arbitrage risk (Ackert and Tian 2000, Wurgler and Zhuravskaya 2002, Pontiff and Schill 2004, Mashruwala et al. 2006).

In a recent study of PEAD, Mendenhall (2004) finds that the strength of post-earnings announcement drift is positively related to arbitrage risk, lending direct support to our conjecture that this factor negatively affects the efficiency of the market's reaction to earnings news. In his study, arbitrage risk is measured by the volatility of residuals from a traditional market model regression. This estimation method is widely used in the literature because it can be easily implemented without significant loss of accuracy relative to more complicated methods.[31] We follow the literature and adopt a market model regression approach to estimating a stock's arbitrage risk. In particular, we estimate the following model:

$$R_{j,t} - rf_t = \alpha_i + \beta_i \cdot (R_{m,t} - rf_t) + \varepsilon_{i,t}\,, \tag{16}$$

where $R_{j,t}$ is the daily return on the portfolio, $rf_t$ is the one-month Treasury bill rate, and $R_{m,t}$ is the daily return on the equal-weighted CRSP universe. Equation (14) is estimated for each portfolio using daily returns[32] over a 252 trading day period that ends on the last day of the calendar month before the earnings announcement. The arbitrage risk variable (ARBRISK) is measured as the variance of the residuals from regression (14), and is expected to have a negative impact on the level of market efficiency in response to earnings news.[33]

Panel A of Table 3 presents summary statistics for the entire sample. On average, the firms in our sample have a market capitalization of 2.61 billion, more than six analysts

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[31] Wurgler and Zhuravskaya (2002) compare two estimates of company-specific arbitrage risk, one using the simple single-factor market model, and one using a much more complex three-factor model incorporating industry, size, and book-to-market. They find that these two estimates have a cross-sectional correlation of as high as 0.98, and produce similar results.

[32] Prior studies, including Mendenhall (2004) and Mashruwala et al. (2006), find that estimation results are insensitive to the return accumulation periods used. Also, using daily returns only requires the stock to be in existence in the databases for at least one year. This is an advantage over using weekly or monthly returns, which normally require at least 3 to 4 years of historical data to run the regression.

[33] Note that due to diversification effects, one cannot use the average of the arbitrage risk for individual stocks as the arbitrage risk for the portfolio.

issuing quarterly earnings forecasts, monthly dollar trading volume of 2.1 million, and institutional ownership of 47%. Panels B and C present the sub-sample summary statistics for good news announcements and bad news announcements, respectively. Compared to good news, bad news appears to be more difficult to forecast, as can be seen from the larger absolute value forecast error and higher dispersion of analysts' opinions. Also, companies in the bad news sub-sample are on average smaller, followed by fewer analysts, less actively traded, and more volatile.

<Please insert Table 3 here>

In equation (4) we use unexpected earnings (*SUE*) as the sole explanatory factor for the price movement at earnings announcement, subjecting the model to potential omitted variable problem. Ideally the effect of these potentially omitted variables would be picked up by the noise residual $v$ alone. However, to the extent that the decomposition of total residual into the noise component ($v$) and inefficiency component ($u$) is less than perfect, our inefficiency estimate $u$ would also be affected by these omitted variables. Moreover, it is not known a priori whether the factors that we examine as determinants of market efficiency are among those "omitted" variables. If this happens to be the case, then true impact of these factors on our market efficiency estimate would not be directly observed by simply correlating the pairs of variables. To address this issue, we perform partial correlation analyses conditional on the omitted factors. We use the announcement day abnormal return ($|AR|$) as the conditioning variable because the omitted factors are not readily identifiable but their joint impact must be reflected by the price movement at earnings announcement.

Table 4 presents the partial Spearman correlations between *ME* and the determinant variables after controlling for |*AR*|, with Panels A and B giving results on the good and bad news sub-samples, respectively. The table shows that the effects on market efficiency of the variables examined are all consistent with our predictions. In particular, the efficiency of market reactions to earnings is higher for firms with higher market value (*MV*), more analyst coverage (*NUMEST*), smaller dispersion of opinions (*STDEV*), higher trading volume (*DVOL*), higher share price (*PRC*), lower arbitrage risk (*ARBRISK*), higher institutional ownership (*INST*), and higher liquidity (*ILLIQ*). In addition, with the exception of arbitrage risk for the good news sub-sample, these relations are all statistically significant for both the good new and bad news sub-samples. Therefore, our results show that size, information environment, cost of trading, and limits of arbitrage are among the economic factors that affect market efficiency.

### *5.3. Under-reaction and post-earnings announcement drift*

The results reported so far have mainly centered on exploring characteristics of market efficiency. Another important issue that remains to be addressed is the magnitude of under-reaction. In this section we test the accuracy of our under-reaction estimates by examining their predictive power for post-announcement abnormal returns. To the extent that the observed PEAD is a correction of the temporary mis-pricing at earnings announcement, our estimates of under-reaction (*UR*) should be able to predict the direction and strength of price movement in the post-event period. Furthermore, *UR* should do a better job than *SUE* in predicting PEAD, because as equations (3) and (11) show, *UR* factors in *ME*, and thus more accurately captures the magnitude of mis-pricing. To examine whether this is the case, we run a horserace by regressing the post-announcement cumulative returns on both variables to see whether the predictive power of *SUE* is subsumed by *UR*:

$$CAR(n)_{i,t} = \alpha + \beta \cdot SUE_{i,t} + \gamma \cdot UR_{i,t} + \varepsilon_{i,t}. \qquad (17)$$

As discussed earlier, a major difficulty in estimating abnormal post-announcement returns is that we have little guidance as to how long the return should be cumulated. For completeness, we report results for one to twenty-four months after the month of announcement. As such, the left-hand side of equation (17) (*CAR(n)*) is the cumulative monthly abnormal return from the first month to the $n^{\text{th}}$ month after the month of earnings announcement, and the regressors *SUE* and *UR* are both as previously defined. We use size-adjusted returns as the abnormal returns to be consistent with prior PEAD studies.[34] The monthly abnormal returns are then summed over the accumulation period to obtain cumulative abnormal returns (*CAR*). Panel A of Table 5 gives the summary statistics of the cumulative abnormal returns in the post-announcement period.

<Please insert Table 5 here>

Panel B of Table 5 presents the regression results of equation (17). For comparison, the left column gives the results for the case in which only *SUE* is included as an independent variable, the middle column reports the results for the case in which both *SUE* and *UR* are included, and the right column gives the results for the case in which only *UR* is included. The left column displays a typical pattern of post-announcement drift, as evidenced by the significantly positive coefficients on *SUE*. However, when *UR* is added

[34] We use the return on the size decile portfolio in which the firm is a member to adjust the raw return. The monthly size decile return data are from the CRSP monthly file.

in the regression, as shown in the middle column of Table 5, the coefficients on *SUE* mostly lose their statistical significance. In contrast, *UR* now takes over from *SUE* most of the predictive power for future returns. From this horserace test, it is apparent that *UR* is more closely correlated with post-announcement returns than unexpected earnings. The right column of the table reports the results when only *UR* is included in the regression. Since *UR* is our direct estimate of the magnitude of investors' under-reaction to earnings news at announcements, the coefficient estimates on the regressor *UR* can be interpreted as the proportion of under-reaction that has been corrected over time. We can see from the column, as well as from Figure 2, that the coefficient grows monotonically until around eight months after the earnings announcement, when it reaches unity, suggesting that the temporary mis-pricing at the announcement has been fully corrected. After that point, there is no explicit pattern exists in the changes in the coefficient estimates. Therefore, our results suggest that the cumulative returns for the first nine months in the post-announcement period are most closely correlated with investors' under-reaction at announcements, and hence may be used as a simple empirical measure of the magnitude of under-reaction.

## 6. Summary and conclusion

In this study we estimate the degree of market efficiency by modeling the earnings-return relation with a stochastic frontier approach. For a sample of 1,251 portfolios representing over 110,000 quarterly earnings announcements from 1985 to 2005, the equally weighted mean of our market efficiency estimates is about 50%, meaning that on average market reactions during the 3-day announcement window recognize only half of the full implications of earning news. Using stock returns as an alternative gauge of the magnitude of the inefficiency, our analyses show that investors' under-reaction to earnings news predicts abnormal returns in the post-announcement period of as much as 11.2%, assuming that the temporary mis-pricing will ultimately be corrected in the long run. We also investigate the determinants of the variation in market efficiency, and find that the market is on average more efficient for firms with higher market capitalization, more analyst coverage, lower transaction cost, less information uncertainty, higher institutional ownership, higher liquidity, and lower arbitrage risk. Finally, we document a strong and positive correlation between our estimate of under-reaction and post-announcement abnormal returns, and find that this correlation largely subsumes the ability of unexpected earnings to predict future returns.

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## Table 1 Summary Statistics of Sample Portfolios

Panel A presents the summary statistics of the variables used in the earnings-return regression. Panel B presents the OLS regression results of the log-transformed earnings-return model $lxret = \alpha + \beta \cdot lsue + \varepsilon$ . Panel C presents the summary statistics of the OLS regression residuals from the model $lxret = \alpha + \beta \cdot lsue + \varepsilon$ . A negatively skewed OLS residual is consistent with the existence of under-reaction. The Shapiro-Wilk test is used to test for normality. *** denotes significant at the 1% level.

### Panel A. Summary Statistics

Good News (SUE>0; N=689)

| Variable | Mean | Median | Std Dev | Q1 | Q3 | 10% | 90% |
|---|---|---|---|---|---|---|---|
| SUE | 0.005 | 0.002 | 0.009 | 0.001 | 0.004 | 0.000 | 0.015 |
| AR | 0.021 | 0.018 | 0.014 | 0.010 | 0.029 | 0.004 | 0.039 |
| LOG(\|SUE\|) | -6.232 | -6.397 | 1.429 | -7.177 | -5.548 | -7.857 | -4.170 |
| LOG(\|AR\|) | -4.197 | -3.990 | 0.970 | -4.591 | -3.533 | -5.455 | -3.237 |

Bad News (SUE<0; N=562)

| Variable | Mean | Median | Std Dev | Q1 | Q3 | 10% | 90% |
|---|---|---|---|---|---|---|---|
| SUE | -0.013 | -0.003 | 0.022 | -0.011 | -0.001 | -0.044 | -0.000 |
| AR | -0.018 | -0.015 | 0.014 | -0.025 | -0.008 | -0.037 | -0.004 |
| LOG(\|SUE\|) | -5.850 | -5.932 | 1.994 | -6.987 | -4.473 | -7.994 | -3.121 |
| LOG(\|AR\|) | -4.342 | -4.197 | 0.956 | -4.852 | -3.685 | -5.587 | -3.306 |

Correlation between LOG(|SUE|) and LOG(|AR|)

| | |
|---|---|
| (Good News Sample; N=689) | 0.535 |
| (Bad News Sample; N=562) | 0.430 |

**Panel B. OLS Regression Results**

| News | Sample Size | Intercept | Log(\|SUE\|) | Adj-$R^2$ | F-stat |
|---|---|---|---|---|---|
| Good (SUE>0) | 689 | -1.933<br>(-13.8) | 0.363<br>(16.6) | 0.286 | 275.6 |
| Bad (SUE<0) | 562 | -3.137<br>(-27.7) | 0.206<br>(11.3) | 0.183 | 126.8 |

**Panel C. Test of Existence of Under-reaction -- Skewness and Normality Test**

| News | Sample Size | Mean | Skewness | Variance | Normality Test | Significance (Normality Test) |
|---|---|---|---|---|---|---|
| Good (SUE>0) | 689 | 0 | -1.768 | 0.671 | 0.871 | *** |
| Bad (SUE<0) | 562 | 0 | -1.275 | 0.746 | 0.926 | *** |

## Table 2 Parameter Estimates of Stochastic Frontier Model

Panel A presents parameter estimates for the good/bad news sub-samples. Alpha, Beta, Sigma, Lamda, Sigma_V, and Sigma_U are Maximum Likelihood estimates of parameters defined in equation (7), $\ln L = C - N\ln\sigma + \sum_{i,t}\ln\Phi(-\frac{\varepsilon_{i,t}\cdot\lambda}{\sigma}) - \frac{1}{2\sigma^2}\sum_{i,t}\varepsilon_{i,t}^2$. ME_LT is the estimate of average market efficiency using equation (8), $E(ME_{i,t}) = E(\exp(-u_{i,t})) = 2[1-\Phi(\sigma_u)]\cdot\exp(\sigma_u^2/2)$. Alpha_OLS, and Beta_OLS are OLS parameter estimates of the model $lxret = \alpha + \beta\cdot lsue + \varepsilon$. Panels B and C present the descriptive statistics of market efficiency (ME) and under-reaction (UR), respectively, for the good/bad news sub-samples. *ME* is calculated by equation (10), $E[ME_{i,t} \mid \varepsilon_{i,t}] = \{\frac{1-\Phi[\sigma_* - (\mu_{i,t}^*/\sigma_*)]}{1-\Phi(-\mu_{i,t}^*/\sigma_*)}\}\cdot\exp(-\mu_{i,t}^* + \frac{1}{2}\sigma_*^2)$. *UR* is calculated by equation (11), $UR_{i,t} = (\frac{1}{ME_{i,t}} - 1)\cdot AR_{i,t}$.

**Panel A. Parameter Estimates for the Stochastic Frontier Model**

| Parameters | Good News (SUE>0 N=689) | Bad News (SUE<0 N=562) |
|---|---|---|
| Alpha | -1.825 | -2.393 |
| Beta | 0.232 | 0.159 |
| Sigma | 1.252 | 1.339 |
| Lamda | 4.419 | 4.270 |
| Sigma_V | 0.276 | 0.305 |
| Sigma_U | 1.221 | 1.303 |
| ME_LT | 0.468 | 0.450 |
| Alpha_OLS | -1.933 | -3.137 |
| Beta_OLS | 0.363 | 0.206 |

**Panel B. Summary statistics of portfolio-specific market efficiency estimates**

| News | Mean | Median | Std Dev | Q1 | Q3 | Max | Min |
|---|---|---|---|---|---|---|---|
| Good News (SUE>0; N=689) | 0.505 | 0.502 | 0.256 | 0.310 | 0.691 | 0.988 | 0.007 |
| Bad News (SUE<0; N=562) | 0.474 | 0.453 | 0.266 | 0.255 | 0.680 | 0.986 | 0.006 |

**Panel C. Summary statistics of portfolio-specific under-reaction estimates**

| News | Mean | Median | Std Dev | Q1 | Q3 | Max | Min |
|---|---|---|---|---|---|---|---|
| Good News (SUE>0; N=689) | -0.018 | -0.018 | 0.010 | -0.024 | -0.011 | 0.000 | -0.049 |
| Bad News (SUE<0; N=562) | -0.018 | -0.018 | 0.010 | -0.024 | -0.011 | 0.000 | -0.049 |

# Table 3 Summary Statistics

The table reports summary statistics of variables used in the test for determinants of market efficiency. *ME* is market efficiency as calculated by equation (10), $E[ME_{i,t} \mid \varepsilon_{i,t}] = \{\frac{1-\Phi[\sigma_* - (\mu^*_{i,t}/\sigma_*))}{1-\Phi(-\mu^*_{i,t}/\sigma_*)}\} \cdot \exp(-\mu^*_{i,t} + \frac{1}{2}\sigma^2_*)$ . *SUE* is standardized unexpected earnings, calculated as I/B/E/S actual EPS minus mean EPS estimates in the I/B/E/S summary file, deflated by the closing price two days before the earnings announcement date. *AR* is abnormal returns at earnings announcement, calculated as the compounded size-adjusted return from day -1 to day 1, where day 0 refers to the earnings announcement date on the I/B/E/S summary file. *MV* is the market value of equity as of the beginning of the month of the earnings announcement. *NUMEST* is the number of earnings estimates included in calculating the consensus forecast in the I/B/E/S summary file. *STDEV* is the standard deviation of all earnings estimates that are used in calculating the consensus forecast in the I/B/E/S summary file. *PRC* is the average closing price over the twelve months before the month of the earnings announcement. *DVOL* is the average monthly dollar trading volume over the twelve months before the month of the earnings announcement. *INST* is institutional ownership, calculated as the percentage of shares held by institutional investors as of the beginning of the month of the earnings announcement. *ARBRISK* is arbitrage risk, calculated as the variance of the residuals from a market model regression, using daily returns over the twelve months before the month of the earnings announcement. *ILLIQ* is illiquidity, calculated using the Amihud (2002) method $ILLIQ = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6$.

**Panel A. Good News Sub-sample (SUE>0; N=689)**

| Variable | Mean | Median | Std Dev | Lower Quartile | Upper Quartile |
|---|---|---|---|---|---|
| SUE | -0.013 | -0.003 | 0.022 | -0.011 | -0.001 |
| AR | -0.018 | -0.015 | 0.014 | -0.025 | -0.008 |
| MV | 2.297 | 1.594 | 2.350 | 0.863 | 2.785 |
| PRC | 23.337 | 23.070 | 9.469 | 15.907 | 30.327 |
| DVOL | 1.772 | 1.100 | 1.912 | 0.717 | 1.963 |
| STDEV | 0.006 | 0.002 | 0.009 | 0.001 | 0.006 |
| NUMEST | 5.850 | 5.708 | 1.530 | 4.774 | 6.794 |
| INST | 0.452 | 0.434 | 0.084 | 0.399 | 0.501 |
| ARBRISK | 0.026 | 0.019 | 0.019 | 0.013 | 0.031 |
| ILLIQ | 0.267 | 0.172 | 0.281 | 0.076 | 0.345 |

**Panel B. Bad News Sub-sample (SUE<0; N=562)**

| Variable | Mean | Median | Std Dev | Lower Quartile | Upper Quartile |
|---|---|---|---|---|---|
| SUE | 0.005 | 0.002 | 0.009 | 0.001 | 0.004 |
| AR | 0.021 | 0.018 | 0.014 | 0.010 | 0.029 |
| MV | 2.859 | 1.998 | 2.793 | 1.133 | 3.365 |
| PRC | 36.955 | 26.590 | 116.921 | 21.002 | 32.835 |
| DVOL | 2.373 | 1.453 | 2.404 | 0.868 | 2.925 |
| STDEV | 0.003 | 0.001 | 0.005 | 0.001 | 0.003 |
| NUMEST | 6.435 | 6.236 | 1.707 | 5.250 | 7.383 |
| INST | 0.494 | 0.472 | 0.095 | 0.425 | 0.550 |
| ARBRISK | 0.026 | 0.019 | 0.018 | 0.013 | 0.032 |
| ILLIQ | 0.194 | 0.120 | 0.215 | 0.056 | 0.252 |

## Table 4 Partial Correlation Matrix

This table presents the spearman partial correlations between market efficiency and its determinants conditional on the absolute value of abnormal return |*AR*|. *ME* is market efficiency as calculated by equation (10), $E[ME_{i,t} \mid \varepsilon_{i,t}] = \{\frac{1-\Phi[\sigma_* - (\mu^*_{i,t}/\sigma_*))}{1-\Phi(-\mu^*_{i,t}/\sigma_*)}\} \cdot \exp(-\mu^*_{i,t} + \frac{1}{2}\sigma^2_*)$. *AR* is abnormal returns at earnings announcement, calculated as the compounded size-adjusted return from day -1 to day 1, where day 0 refers to the earnings announcement date on the I/B/E/S summary file. |*AR*| is the absolute value of *AR*. *MV* is the market value of equity as of the beginning of the month of the earnings announcement. *NUMEST* is the number of earnings estimates included in calculating the consensus forecast in the I/B/E/S summary file. *STDEV* is the standard deviation of all earnings estimates that are used in calculating the consensus forecast in the I/B/E/S summary file. *PRC* is the average closing price over the twelve months before the month of the earnings announcement. *DVOL* is the average monthly dollar trading volume over the twelve months before the month of the earnings announcement. *INST* is institutional ownership, calculated as the percentage of shares held by institutional investors as of the beginning of the month of the earnings announcement. *ARBRISK* is arbitrage risk, calculated as the variance of the residuals from a market model regression, using daily returns over the twelve months before the month of the earnings announcement. *ILLIQ* is illiquidity, calculated using the Amihud (2002) method $ILLIQ = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6$.

All correlations are statistically significant at the 1% level except those marked with a, which is significant at the 5% level, b, which is significant at the 10% level, and c, which is not significant at conventional levels.

**Panel A. Good News Sub-sample (SUE>0; N=689)**

| | ME | MV | DVOL | PRC | STDEV | NUMEST | INST | ARBRISK | LIQ |
|---|---|---|---|---|---|---|---|---|---|
| ME | 1.000 | | | | | | | | |
| MV | 0.454 | 1.000 | | | | | | | |
| DVOL | 0.347 | 0.850 | 1.000 | | | | | | |
| PRC | 0.459 | 0.611 | 0.312 | 1.000 | | | | | |
| STDEV | -0.745 | -0.583 | -0.548 | -0.473 | 1.000 | | | | |
| NUMEST | 0.450 | 0.800 | 0.783 | 0.448 | -0.573 | 1.000 | | | |
| INST | 0.419 | 0.620 | 0.759 | 0.191 | -0.626 | 0.741 | 1.000 | | |
| ARBRISK | -0.062 [c] | -0.202 | -0.009[c] | -0.289 | 0.066 [b] | -0.055 [c] | -0.077 [a] | 1.000 | |
| ILLIQ | -0.335 | -0.636 | -0.691 | -0.447 | 0.481 | -0.631 | -0.651 | 0.157 | 1.000 |

**Panel B. Bad News Sub-sample (SUE<0; N=562)**

| | ME | MV | DVOL | PRC | STDEV | NUMEST | INST | ARBRISK | ILLIQ |
|---|---|---|---|---|---|---|---|---|---|
| ME | 1.000 | | | | | | | | |
| MV | 0.632 | 1.000 | | | | | | | |
| DVOL | 0.586 | 0.871 | 1.000 | | | | | | |
| PRC | 0.504 | 0.754 | 0.521 | 1.000 | | | | | |
| STDEV | -0.804 | -0.728 | -0.633 | -0.684 | 1.000 | | | | |
| NUMEST | 0.634 | 0.851 | 0.764 | 0.687 | -0.739 | 1.000 | | | |
| INST | 0.619 | 0.691 | 0.747 | 0.452 | -0.687 | 0.755 | 1.000 | | |
| ARBRISK | -0.155 | -0.287 | -0.129 | -0.377 | 0.228 | -0.222 | -0.171 | 1.000 | |
| ILLIQ | -0.516 | -0.666 | -0.679 | -0.642 | 0.579 | -0.600 | -0.631 | 0.274 | 1.000 |

## Table 5
## Under-reaction and Post-earnings Announcement Drift

Panel A gives the summary statistics of the size-adjusted cumulative return from one to twenty-four months after the month of earnings announcements. Panel B gives the coefficient estimates of the model $CAR(n) = \alpha + \beta \cdot SUE + \gamma \cdot UR + \varepsilon$. *UR* is the magnitude of under-reaction as calculated by equation (11), $UR_{i,t} = (\frac{1}{ME_{i,t}} - 1) \cdot AR_{i,t}$ . *SUE* is standardized unexpected earnings, calculated as the I/B/E/S actual EPS minus mean EPS estimates in the I/B/E/S summary file, deflated by the closing price two days before the earnings announcement date. *CAR(n)* is the cumulative monthly size-adjusted abnormal return from the first month to the $n^{th}$ month after the month of the earnings announcement. The left column reports results when only *SUE* is included in the regression. The middle column reports results when both *SUE* and *UR* are included in the regression. The right column reports results when only *UR* is included in the regression. *, **, *** denote statistically significant at the 10%, 5%, and 1% level, respectively.

**Panel A. Summary Statistics**

| | Good News Sample (SUE>0; N=689) | | | | | Bad News Sample (SUE<0; N=562) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| CAR (%) | Mean | Median | Q1 | Q3 | Std Dev | Mean | Median | Q1 | Q3 | Std Dev |
| 1 | 0.66 | 0.54 | -0.55 | 1.90 | 2.80 | -0.38 | -0.14 | -1.56 | 0.90 | 2.94 |
| 2 | 0.92 | 1.03 | -1.07 | 2.86 | 3.88 | -1.01 | -0.87 | -2.83 | 0.95 | 4.10 |
| 3 | 1.52 | 1.44 | -1.17 | 4.13 | 4.81 | -1.01 | -0.83 | -3.67 | 1.73 | 5.35 |
| 4 | 1.58 | 1.60 | -1.44 | 4.47 | 5.36 | -1.03 | -0.50 | -3.70 | 2.15 | 6.42 |
| 5 | 1.53 | 1.33 | -1.55 | 4.76 | 6.03 | -1.48 | -1.06 | -4.91 | 2.02 | 6.73 |
| 6 | 1.89 | 1.81 | -1.44 | 5.36 | 6.41 | -1.16 | -0.90 | -4.57 | 2.42 | 7.11 |
| 7 | 2.06 | 2.17 | -1.65 | 5.73 | 6.83 | -1.38 | -0.82 | -4.88 | 2.65 | 8.18 |
| 8 | 2.00 | 2.10 | -1.89 | 5.97 | 7.54 | -1.79 | -1.30 | -5.53 | 2.50 | 8.72 |
| 9 | 2.36 | 2.30 | -1.54 | 6.73 | 8.16 | -1.54 | -1.27 | -5.57 | 2.83 | 9.47 |
| 10 | 2.62 | 2.70 | -1.48 | 7.19 | 8.56 | -1.23 | -0.86 | -5.53 | 3.08 | 10.07 |
| 11 | 2.56 | 2.33 | -1.75 | 7.12 | 8.87 | -1.48 | -1.50 | -6.37 | 3.19 | 10.69 |
| 12 | 3.19 | 2.97 | -1.53 | 7.96 | 9.07 | -0.98 | -1.37 | -5.82 | 3.91 | 10.90 |
| 13 | 3.30 | 3.05 | -1.38 | 8.04 | 9.59 | -0.75 | -0.74 | -5.44 | 4.50 | 11.42 |
| 14 | 3.17 | 3.28 | -1.46 | 7.85 | 10.03 | -0.60 | -0.71 | -5.73 | 4.68 | 11.24 |
| 15 | 3.76 | 3.60 | -1.15 | 8.57 | 10.64 | -0.09 | -0.09 | -5.42 | 4.77 | 11.78 |
| 16 | 3.95 | 3.76 | -1.37 | 9.48 | 11.05 | 0.02 | -0.15 | -5.68 | 4.72 | 12.30 |
| 17 | 3.71 | 3.53 | -1.77 | 9.30 | 11.53 | 0.03 | -0.09 | -5.65 | 5.00 | 12.58 |
| 18 | 4.31 | 3.92 | -1.89 | 9.90 | 11.73 | 0.55 | 0.10 | -5.46 | 5.38 | 12.77 |
| 19 | 4.57 | 4.28 | -1.61 | 10.55 | 11.99 | 0.72 | 0.54 | -5.08 | 6.12 | 13.07 |
| 20 | 4.53 | 3.93 | -1.77 | 10.69 | 12.38 | 0.84 | 0.61 | -5.11 | 6.35 | 13.29 |
| 21 | 5.15 | 4.62 | -1.81 | 11.47 | 13.12 | 1.48 | 1.39 | -4.84 | 7.04 | 13.37 |
| 22 | 5.60 | 5.24 | -1.41 | 12.67 | 13.57 | 1.80 | 1.50 | -4.89 | 7.71 | 13.68 |
| 23 | 5.48 | 4.88 | -1.44 | 12.89 | 13.79 | 1.54 | 1.51 | -4.84 | 7.88 | 13.85 |
| 24 | 6.62 | 5.71 | -1.05 | 13.76 | 13.89 | 2.16 | 1.67 | -4.78 | 8.38 | 14.03 |

**Panel B Regression Results**

| | MODEL1 | MODEL2 | | MODEL3 |
|---|---|---|---|---|
| **CAR (n)** | **SUE** | **UR** | **SUE** | **UR** |
| 1 | 0.293*** | 0.031 | 0.274*** | 0.171*** |
| 2 | 0.324*** | 0.351*** | 0.102 | 0.403*** |
| 3 | 0.437*** | 0.560*** | 0.081 | 0.602*** |
| 4 | 0.522*** | 0.521*** | 0.191* | 0.619*** |
| 5 | 0.566*** | 0.697*** | 0.124 | 0.760*** |
| 6 | 0.636*** | 0.747*** | 0.162 | 0.830*** |
| 7 | 0.827*** | 0.706*** | 0.379*** | 0.900*** |
| 8 | 0.880*** | 0.817*** | 0.362** | 1.002*** |
| 9 | 0.938*** | 0.828*** | 0.413** | 1.039*** |
| 10 | 0.888*** | 0.860*** | 0.342* | 1.035*** |
| 11 | 0.931*** | 0.896*** | 0.363* | 1.081*** |
| 12 | 0.913*** | 0.920*** | 0.329* | 1.088*** |
| 13 | 1.010*** | 0.811*** | 0.495** | 1.065*** |
| 14 | 0.893*** | 0.801*** | 0.385* | 0.998*** |
| 15 | 0.839*** | 0.868*** | 0.288 | 1.016*** |
| 16 | 0.910*** | 0.852*** | 0.369* | 1.041*** |
| 17 | 0.840*** | 0.916*** | 0.259 | 1.049*** |
| 18 | 0.820*** | 0.954*** | 0.214 | 1.064*** |
| 19 | 0.863*** | 0.880*** | 0.305 | 1.036*** |
| 20 | 0.734*** | 0.911*** | 0.156 | 0.991*** |
| 21 | 0.773*** | 0.911*** | 0.195 | 1.010*** |
| 22 | 0.738*** | 0.972*** | 0.121 | 1.034*** |
| 23 | 0.784*** | 0.993*** | 0.154 | 1.072*** |
| 24 | 0.840*** | 1.035*** | 0.183 | 1.129*** |

**Figure 1**
**Distribution of Quarterly Earnings Announcements by Month**

The figure displays the distribution of quarterly earnings announcements by month from 1985 to 2005. Earnings announcement dates come from the I/B/E/S summary file.

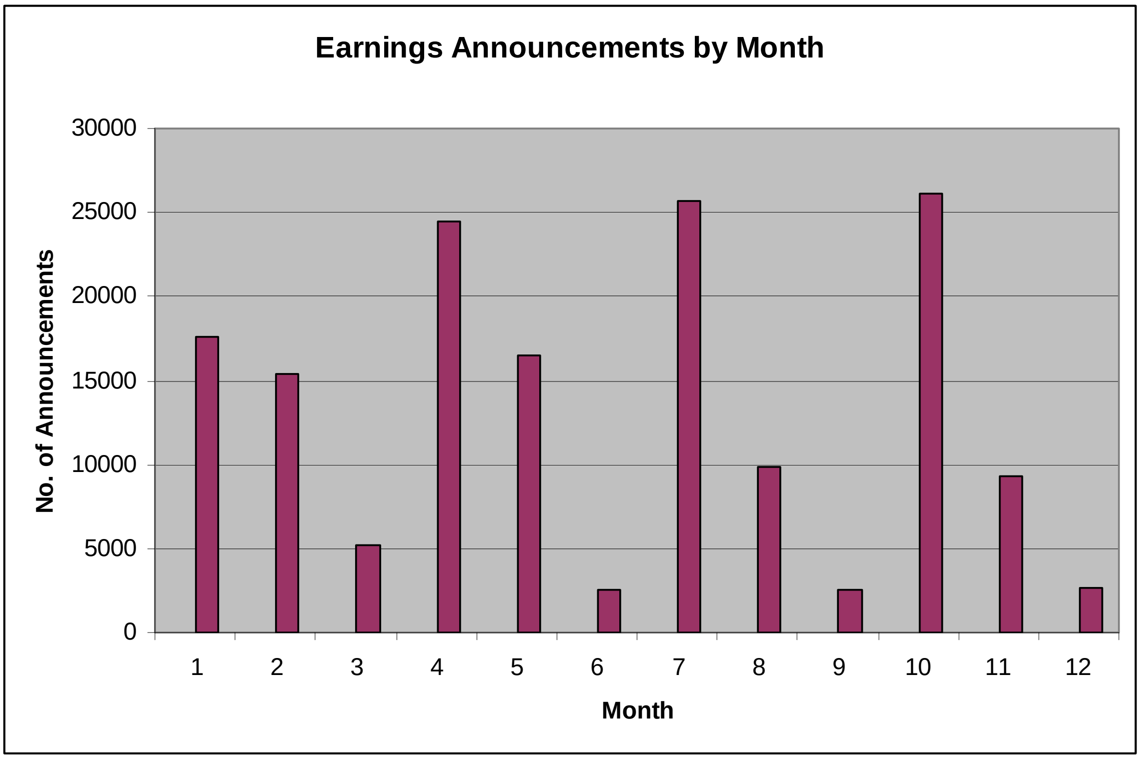

**Figure 2**
**Under-reaction and Post-earnings announcement drift**

The figure displays the coefficient estimates of the regression $CAR(n) = \alpha + \beta \cdot UR + \varepsilon$. *UR* is the magnitude of under-reaction as calculated by equation (11), $UR_{i,t} = (\frac{1}{ME_{i,t}} - 1) \cdot AR_{i,t}$. *CAR(n)* is the cumulative monthly size-adjusted abnormal return from the first month to the $n^{th}$ month after the month of the earnings announcement.