The Fraud-on-the-Market Theory and the Indicators of Common Stocks’ Efficiency

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ABSTRACT

In Basic, Inc. v. Levinson, the Supreme Court revolutionized securities (10b-5) litigation by upholding the principle that the reliance requirement (i.e., plaintiff relied on the alleged misrepresentation in making the investment decision) can be disposed of in efficient capital markets. This principle, known as the fraud-on-the-market theory, thus shifts the focus from an individual’s reliance on a misrepresentation (fraud) to the effect of the misrepresentation on the security’s price, and the individual’s reliance on this price (the integrity of the market). In upholding the fraud-on-the-market principle, the Supreme Court required plaintiffs to prove that the litigated securities were traded in an efficient market, though it did not elaborate on the specific means by which market efficiency can be proved or disproved.

In the aftermath of Basic, Inc. v. Levinson, lower courts grappled numerous times with market efficiency proofs without much success. Ad hoc indicators, such as the number of market makers in the security and the exchange on which the security is traded were considered without substantive, widely-accepted conclusions.

This study is the first to provide comprehensive empirical evidence on the specific indicators of market efficiency, thus filling the void created by the need to prove market efficiency. Specifically, this research identifies eight potential “efficiency” drivers and examines the ability of these efficiency drivers to differentiate a sample of inefficiently priced common stocks from a sample of efficiently priced common stocks. Whether a stock is inefficiently priced is based on the lack of price response to an announcement of an extreme earnings surprise.

We find two such factors that systematically differentiate between efficiently and inefficiently priced stocks, namely, the volume of trade and the

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number of analysts following the security. Surprisingly, several presumed efficiency indicators that were used by courts, the number of market makers, in particular, failed in our tests to discriminate between efficiently and inefficiently priced securities. We also provide practical guidelines regarding the application of the identified efficiency drivers in specific litigation.

With no staff economists, no experts schooled in the "efficient-capital-market hypothesis," no ability to test the validity of empirical market studies, we are not well equipped to embrace novel constructions of a statute based on contemporary microeconomic theory.¹

I. INTRODUCTION

This paper develops and sets forth specific indicators that systematically distinguish between stocks that are efficiently versus inefficiently priced. While this distinction is important for managers, investors, and others who make decisions conditional on such, it has become a crucial aspect of, and has fundamentally changed, the application of Securities and Exchange Commission (SEC) Rule 10b-5.²

Traditionally, plaintiffs in securities fraud cases had to show that in making an investment decision they relied on the alleged misrepresentation by the defendants, in addition to proving the existence of a misrepresentation or omission of facts (which defendants had a duty to disclose), the materiality of the misrepresentation, the defendants' intent or recklessness in making the misrepresentation (scienter), and the damage suffered by plaintiffs.³ “Reliance” in this context means that plaintiffs considered the misrepresentation a substantial factor in making their investment decision.⁴

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2. 17 C.F.R. § 240.10b-5 (1992). Rule 10b-5 provides:
   It shall be unlawful for any person, directly or indirectly, by the use of any means or instrumentality of interstate commerce, or of the mails or of any facility of any national securities exchange,
   (a) To employ any device, scheme, or artifice to defraud,
   (b) To make any untrue statement of a material fact or to omit to state a material fact necessary in order to make statements made, in the light of the circumstances under which they were made, not misleading, or
   (c) To engage in any act, practice, or course of business which operates or would operate as a fraud or deceit upon any person, in connection with the purchase or sale of any security.
3. Id.; See ALAN R. BROMBERG & LEWIS D. LOWENFELS, SECURITIES FRAUD & COMMODITIES FRAUD § 2.5(6) (1988) (estimating that of the actions brought under the federal securities statutes, about one-third involve Rule 10b-5).
5. Ernst & Young v. Hochfelder, 425 U.S. 185, 206, reh'g denied, 425 U.S. 986 (1976); Lipton v.
This is the case, for example, when plaintiffs analyzed the firm’s financial reports containing the alleged misrepresentation, and this analysis contributed to their decision to purchase the securities.\(^5\)

Proving reliance was a considerable stumbling block for plaintiffs, particularly at the class certification stage, since most investors do not read, let alone thoroughly analyze financial statements, prospectuses, or other corporate disclosures. Thus, defendants in 10b-5 misrepresentation cases objected successfully to many class certifications by providing evidence that some class members had not read or did not have the professional ability to comprehend the financial reports containing the alleged misrepresentation, thereby claiming that plaintiffs failed to show reliance.\(^6\)

Legal attitude towards reliance changed drastically in the early 1980s as courts were presented with the efficient capital markets (ECM) theory, developed some two decades earlier by financial economists, as an alternative to the reliance requirement.\(^7\) In efficient capital markets, it was argued, security prices reflect at any point in time the information (including misinformation) that is publicly available about securities.\(^8\) Therefore, it is irrelevant whether an investor actually relied on a specific source of information or not, since the price an investor paid (or received) for the security already reflected the alleged misrepresentation. Damage was thus caused to investors by a misrepresentation to efficient markets whether they relied on a specific information source or not.\(^9\) In legal parlance this argument came to be known as the “fraud-on-the-market theory,” enabling plaintiffs to claim reliance upon the “integrity” (efficiency) of the stock price rather than on a specific information source.\(^10\) The fraud-on-the-market theory shifts the focus from an individual’s reliance on a misstatement to the effect of the misstatement on the security’s price and the individual’s presumed reliance on this price.\(^11\) The stock market is said to stand in as an “unpaid agent of investor,”\(^12\) where

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5. See supra notes 3-4.
6. The Supreme Court first abrogated plaintiff’s burden of proving direct reliance in Affiliated Ute Citizens of Utah v. United States, 406 U.S. 128, 153-154 (1972) (“Under the circumstances of this case, involving primarily a failure to disclose, positive proof of reliance is not a prerequisite to recovery. All that is necessary is that the facts withheld be material in the sense that a reasonable investor might have considered them important in the making of this decision.”). See also Mills v. Electric Auto-Lite Co., 396 U.S. 375, 384-85 (1970) (holding that a finding of materiality is a sufficient causal relationship between the violation and the injury).
10. See supra note 9 and accompanying text (discussing the “fraud-on-the-market” theory of reliance, which, unlike direct reliance, presumes reliance on a transaction occurring in an efficient market).
a misrepresentation made to an efficient market is as if it were made to every individual investor in this market.

The Supreme Court examined the fraud-on-the-market theory in *Basic, Inc. v. Levinson*. Basic, Inc. was a large manufacturing company whose stocks were traded on the New York Stock Exchange. Beginning in September 1976, Basic’s officers were involved in merger negotiations with another company, Combustion Engineering. Nevertheless, Basic’s officers made three public statements during 1977 and 1978 denying such negotiations. In December, 1978, Basic’s board approved a tender offer by Combustion Engineering. Basic shareholders who sold shares between the time of the first public denial of merger negotiations and the final approval brought suit under Rule 10b-5 alleging that they were harmed by Basic’s false and misleading statements, which caused the price they obtained for the shares to be artificially depressed. The Supreme Court in *Basic* permitted plaintiffs to employ the fraud-on-the-market theory to meet the reliance requirement. The Supreme Court in *Basic* thus “revolutionized” securities litigation.

While upholding the principle that the reliance requirement can be disposed of in efficient capital markets, the Supreme Court in *Basic* required plaintiffs to show that the litigated securities were traded in an efficient market. However, the Court did not elaborate on the operational means of proving market efficiency. Thus, the applicability of the fraud-on-the-market theory to specific cases remained an open question.

As suggested by Justice White (in our opening quotation), application of the efficient market theory creates both conceptual and practical problems. On the conceptual level, the efficient market theory is still evolving. Practically, specific guidelines are required to determine whether a given security was efficiently traded at a point in time. As to the current state of market efficiency, both economic theory and compre-

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CORNELL L. REV. 907, 907 (1989) (stating that “[t]he fraud-on-the-market theory . . . has shifted the focus from the individual plaintiff to whether a challenged disclosure affected the market as a whole”).


14. *Id.* at 227.

15. *Id.*

16. *Id.* at 228.

17. *Id.*


20. Mark Saks, *Corporate Law II: The Supreme Court Examines Rule 10b-5 Actions*, 1989 ANN. SURV. OF AM. L. 639, 664 (1989) (“Nevertheless, the Court’s decision in *Basic* has prompted the development of a judicial test that instructs courts to analyze the market efficiency of securities on an individual basis prior to the application of the fraud-on-the-market theory.”).

21. Jonathan R. Macey, *The Fraud-on-the-Market Theory: Some Preliminary Issues*, 74 CORNELL L. REV. 923, 925 (1989) (stating that “[a]fter *Basic, Inc. v. Levinson*, the issue of whether a particular stock traded in an efficient market will now become an important part of every fraud-on-the-market case . . . . But we have yet to observe a workable test for determining whether the market for a particular security is efficient.”).
bensive empirical evidence strongly suggest that the early concept of market efficiency—that security prices in organized markets reflect at any time all publicly available information—needs to be revised significantly. Even the oft mentioned term "publicly available information" appears ambiguous. Who is the "public"? All investors or just the relatively small number of professionals that actively seek and use information in their trading? It is now widely accepted that different investors are at any point in time endowed with different levels and qualities of information about a given security, and that prices, even in equilibrium, do not necessarily reflect all the information possessed by the informed investors. Stated differently, security prices in general do not perfectly transfer information from the informed to the less informed investors, an assumption that lies at the heart of the legal application of the efficient capital markets theory, as reflected in the statement: "the stock market is an unpaid agent of the investor." It is clear that the efficient capital markets theory is still in a developmental stage, a fact which complicates its application to specific legal cases.

Conceptual difficulties with the efficient capital markets theory notwithstanding, courts in the aftermath of Basic had to grapple with the application of the fraud-on-the-market theory. For example, in Harman v. Lyphomed, Inc. the federal district court stressed that despite the fact the security involved was traded over-the-counter, the stock was priced efficiently. Plaintiffs based their arguments on several characteristics of the litigated security: the stock had trading volume in excess of one million shares per week, had numerous market makers, was followed by financial analysts, and the firm filed the S-3 Form with the SEC. Based on these criteria, the court awarded the plaintiff class the presumption of reliance afforded by the fraud-on-the-market theory. In Cammer v. Bloom, the defendants argued that the Supreme Court intended to apply the fraud-on-the-market theory to litigation involving securities traded on national stock exchanges and not to over-the-counter markets. While the Cammer court rejected the location of the market as an exclusive indicator of its efficiency, it constructively set several guidelines for market efficiency: a substantial trading volume, the existence of several analysts following the stock, the requirement that the stock should be traded by several market makers, and eligibility to file a S-3 registration statement.


24. See Macey et al., supra note 19, at 1025 (stating that "we can at a minimum conclude that substantial disagreement exists among financial economists about what conclusions empirical tests of market efficiency support").


26. The SEC requires no more than S-3 filings from corporations whose shares are actively traded and widely followed. Relatively small, young companies have to file the more extensive Form S-1. See Securities Act of 1933, 15 U.S.C. 77a (providing for Form S-1).


29. Id. at 1281 (stating, "[w]hile the location of where a stock trades might be relevant, it is not dispositive of whether the current price reflects all information").

The various market efficiency criteria applied so far by courts are ad hoc. We know of no systematic body of evidence showing that these or any other criteria distinguish between efficient and inefficient stocks. Nor are we aware of evidence supporting specific cutoff values of these criteria.

This study fills the void created by the Supreme Court decision in Basic, Inc. v. Levinson by providing evidence on the factors that systematically distinguish between efficiently and inefficiently traded stocks. Specifically, based on an operational definition of stock efficiency—a price reaction to the release of significant, unexpected information—we select samples of efficient and inefficient stocks and derive in a statistical multivariate framework a set of factors, or "efficiency drivers," that best discriminates between the two samples. Our findings confirm some efficiency factors used by courts, while finding other factors unsupported by the data. Specifically, volume of trade and number of analysts consistently discriminate between the efficient and inefficient stocks in our sample, while firm size (total market capitalization), a variable that plays a major role in capital market research, does not discriminate between the two samples. Surprisingly, the number of market makers in the stock, a factor which was often used by courts as an important efficiency driver, also failed to discriminate between efficient and inefficient stocks. Other variables examined (bid-ask spread, price volatility, institutional holdings, and stock price) also do not appear to be efficiency drivers.

II. CANDIDATE EFFICIENCY DRIVERS

What are the fundamental factors that determine the degree to which a security is traded efficiently? Posing the question this way makes it clear that efficiency is not a market or an exchange attribute, but rather a characteristic of a given security during a given period of time. Even for a given security and time period, efficiency might vary across different information items. For example, while the market can be efficient with

31. E.g., trading volume, number of analysts and market makers, and eligibility to file Form S-31.
32. For example, a number of cases and commentators have placed considerable weight on form S-3 as the best way for a court to determine market efficiency. See Harman v. Lyphomed, Inc., 122 F.R.D. 522, 525 (N.D. III. 1988) (relying on use of form S-3 to determine market efficiency); Barbara Black, Fraud on the Market: a Criticism of Dispensing with Reliance Requirements in Certain Open Market Transactions, 62 N.C. L. REV. 435, 468-72 (1984) (advocating not to allow fraud-on-the-market theory to be used in cases involving corporations which do not use form S-3); Marvin G. Pickholz & Edward B. Horahan, The SEC's Version of the Efficient Market Theory and Its Impact on Securities Law Liabilities, 39 WASH. & LEE L. REV. 943, 957 (1982) (suggesting that the SEC has provided courts with the means for identifying which securities trade on efficient markets).
33. See, e.g., BROMBERG & LOWENFELS, supra note 2, § 8.6, at 641 ("Turnover measured by average weekly trading of two percent or more of the outstanding shares would justify a strong presumption that the market is efficient.").
34. This is consistent with Cammer which established the efficiency criterion as a "cause and effect relationship between unexpected corporate events or financial releases and an immediate response in the stock price." Cammer, 711 F. Supp. at 1287.
35. See, e.g., BROMBERG & LOWENFELS, supra note 2 § 8.6, at 641 (suggesting that, in Cammer, the existence of ten market makers or more in a security justifies a substantial presumption of efficiency, while five market makers suggest a modest presumption of efficiency).
respect to a widely-used and regularly-reported item, such as earnings, it can be inefficient (react slowly to the release of information) with respect to an infrequent, difficult to interpret item, such as the announcement of a new business alliance.\footnote{36}

A security’s degree of efficiency is an outcome of the competition in the capital markets for the security.\footnote{37} Efficiency drivers are therefore related to factors that reflect or facilitate that competition, such as the availability of information about the security, costs of transacting in the security, number of traders, and volume of trade.\footnote{38} Specifically, we identify the following candidate efficiency drivers for our empirical tests based on financial economic theory. Some of our candidate efficiency drivers have been mentioned by the courts.\footnote{39}

1. **Volume of trade.** The more active the trade in a security, the higher the likelihood that more value-relevant information will be generated about it by analysts, since large volume promises them generous compensation. Moreover, large volume ensures that the information will be quickly and accurately impounded in the security’s price. Volume, as an important indicator of efficiency, has been recognized by courts, for example, in *Cammer v. Bloom*.

2. **Number of market makers.** Over-the-counter market makers, who provide a market for securities, are presumably knowledgeable about the issuing company and the stocks’ supply and demand conditions (i.e., the “order flow”). Therefore, it is believed the larger the number of market makers in a given security, the more information is available about it and the quicker its dissemination in the price. This efficiency driver has been mentioned in several legal proceedings.\footnote{40}

3. **Firm size.** Robinson has suggested firm size as a variable courts might use in assessing a stock’s efficiency.\footnote{41} Many researchers have documented that firm size is an important variable to explain firm behavior and stock returns.\footnote{42} The pervasiveness of firm size as an explanatory variable in financial economics warrants its inclusion in this analysis. *A priori*, we anticipate small firms will be less efficiently priced.

4. **Bid-ask spread and return variability.** These are indicators of “information asymmetries,” namely the availability of superior information to some investors while not to others.\footnote{43} These measures also reflect the security’s liquidity.\footnote{44} In general, the larger

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\footnote{36}{It is even questionable whether the market is efficient with respect to earnings announcements. There is convincing evidence that investors underreact to earnings announcements. See generally Victor L. Bernard and Jacob K. Thomas, *Evidence that Stock Prices Do Not Fully Reflect the Implication of Current Earnings for Future Earnings*, 13 J. ACCT. & ECON. 305, 305-340 (1990).}

\footnote{37}{See Grossman & Stiglitz, supra note 22 (discussing the effects of competition for information on market efficiency).}

\footnote{38}{We select these variables because of their use by courts. See supra note 30 and accompanying text.}


\footnote{40}{See, e.g., Bromberg & Lowenfelds, supra note 2, § 8.6, at 641.}

\footnote{41}{Robinson, supra note 39, at 231 (discussing the “small firm effect”).}


\footnote{43}{For example, in the extreme, information about the prospects of the firm available only to the firm’s managers would represent the most severe form of information asymmetry between a firm’s managers and shareholders.}

\footnote{44}{See, e.g., Yakov Amihud & Haim Mendelson, *Asset Pricing and the Bid-Ask Spread*, 17 J. FIN.
the information asymmetry and the lower the liquidity, the lower will be the degree of the stock's efficiency.45

5. **Price level.** Recent research suggests some of the anomalies attributed to firm size may in fact be related to a stock's price level. In particular, stocks with low price levels appear to behave anomalously.46 If price level is important to the determination of market efficiency, we expect low priced stocks to be less efficiently priced.47

6. **Number of analysts following the stock.** Analysts gather and independently generate information about companies and disseminate such information to their clients (e.g., in the form of earnings forecasts and recommendations). Accordingly, it can be expected that the larger the number of analysts following a security, the more efficiently it is traded. This efficiency driver was mentioned by the *Cammer* court.48

7. **Institutional investment.** Institutional investors (e.g., mutual funds, money managers, banks) are presumed to be better informed about the securities they hold and better able to interpret new information than individual investors.49 Accordingly, the larger the number of institutional investors in a stock or the larger the percentage of stock held by institutions, or both, the more efficient it is expected to be.50

We now turn to testing the validity of the candidate efficiency drivers outlined above. Surprisingly, the importance of such validity tests is not generally appreciated. For example, Robinson, states:

> Despite the efficient market hypothesis’ illusive nature, these factors [efficiency drivers] are readily discernible by a court without resorting to economic statistical models. They can be compared to factors present in markets that are generally accepted as efficient. A court should inquire into such factors when faced with a thinly-traded security.51

This opinion implies that it is sufficient in specific cases to quantify several drivers and compare them with similar measures of efficient stocks, without having to resort to economic statistical models. For example, seven analysts following the security or five market makers in the security might suggest it is efficiently priced. This is obviously inappropriate.

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ECON. 223, 246 (1986) (discussing the link between bid-ask spread, liquidity, and pricing); Lawrence R. Glosten & Paul R. Milgrom, *Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders*, 14 J. FIN. ECON. 71, 76-91 (1985) (presenting basic model in which the bid-ask spread decreases as insiders' information improves or when insiders become more numerous relative to persons who trade for liquidity purposes).


47. *Id.*


49. *See* Charles Lee et al., *Investor Sentiment and the Close-End Fund Puzzle*, 46 J. FIN. 75, 80-86 (1991) (presenting an analysis of noise investors (individuals) and rational investors (institutions) and explaining that closed-end funds may not trade at their net asset value, in part, because of the low ownership of the better informed institutions in closed-end mutual funds).

50. *Id.*

First, absent empirical work, how does one know which of the a priori intuitive efficiency drivers does in fact discriminate between efficient and inefficient securities? The fact that some factors, such as the number of market makers, make intuitive sense does not establish them as efficiency drivers. Second, given that most efficiency drivers are correlated, as the volume of trade and firm size are, they cannot be considered as independent efficiency indicators. For example, given the high correlation between volume or trade and firm size, evidence on the relatively large volume and size of a given stock does not constitute two independent indicators leading to a presumption of efficiency. The two indicators essentially amount to, in this case, one. Again, empirical analysis is called for to determine the extent and implications of such correlations. Third, and most problematic, what if the efficiency drivers in a specific case provide conflicting signals? For example, volume is above the benchmark while the number of market makers is below that of the efficient group. Empirical evidence is again called for to indicate the relative importance of each driver in contributing to efficiency. Thus, application of the fraud-on-the-market theory does require "economic statistical analysis," at least at the preliminary stage of identifying the major efficiency drivers, their inter-dependencies, and their relative contribution to efficiency. We now turn to such an analysis.

III. DATA AND METHODOLOGY

In this section, we set forth operational criteria for determining the efficiency of a security's price, the variables that proxy for the efficiency drivers outlined above, and the sample collection procedures. A priori, we restrict our analysis to NASDAQ (over the counter) securities because we believe more potential dispersion in the efficiency of the pricing of these securities exists than in securities traded on the NYSE or AMEX. To be included in our sample for a given calendar year, 1984-1990, a firm must meet the following criteria:

- Quarterly earnings for firm $i$, $E_{i,t}$, must be available for the current and previous quarter, $t$ and $t-1$, and four and five quarters preceding the current quarter, $t-4$ and $t-5$, from the COMPUSTAT Quarterly data tape.
- Earnings announcement date is available from COMPUSTAT.
- Beginning of quarter stock price and shares outstanding must be available for the current quarter from COMPUSTAT.
- No change in fiscal year for the period under consideration.
- Daily stock returns are available from the Center for Research in Security Prices (CRSP) NASDAQ Daily Return file for the five days surrounding the earnings announcement date.

52. See infra Table IV.
54. We use COMPUSTAT Data Item 8, income before extraordinary items. The data service is provided by Standard & Poor's Compustat Services, a division of McGraw-Hill, Inc.
These sample criteria yield 49,349 firm-quarter observations for the years 1984-1990.

A. The Efficiency Criterion

In an efficient market, all publicly released information should be quickly and fully reflected in the price of a security. Beginning with the work of Ball and Brown, it has been well-established that the announcement of earnings conveys valuable information. Thus, if the market for certain securities is inefficient, the information content of earnings announcements would not be immediately reflected in the price of these securities. We therefore propose to measure the efficiency of a firm's security price by analyzing the stock price response to the announcement of unexpected earnings. Unexpected earnings, namely the extent of new information in an earnings announcement, are defined as the released earnings figure minus a measure of investors' expectations.

Consider two firms, A and B, that announce earnings containing an equally large unexpected component. Other things being equal, if firm A's announcement generates a large price adjustment and firm B's announcement does not, one would tend to conclude that the price of firm B's stock is inefficiently priced. This is the basic intuition behind our measurement of market efficiency.

We chose corporate earnings as the information item signaling efficiency, because earnings information is the most frequently released, widely disseminated, and closely watched information disclosed by public corporations. Earnings information, therefore, sets a lower bound of market efficiency. It is conceivable that a given stock is traded efficiently with respect to earnings (i.e., price reacts quickly and unbiasedly to the release of earnings), but inefficiently with respect to other information items which are more difficult for investors to interpret (i.e., a new business alliance, a new strategic plan).

B. Unexpected Earnings and Abnormal Stock Returns

We use the following model based on differences in quarterly earnings to estimate forecasted earnings:

56. Fischel, supra note 11, at 912, explains:

No clear answer exists to the question of how much and how quickly information has to be incorporated into prices for the fraud on the market theory to apply.

The most that can be said is that the more rapidly prices reflect publicly-available information, the more sensible it is to apply the theory.

Id.


58. Peter Lynch, former manager of Fidelity Magellan, asserts "battalions of analysts and statisticians are launched against the questions of future growth and future earnings." See PETER LYNCH, ONE UP ON WALL STREET 168 (1989). See also PAUL FRISCHKOFF, FINANCIAL ACCOUNTING STANDARDS BOARD, REPORTING OF SUMMARY INDICATORS: AN INVESTIGATION OF RESEARCH AND PRACTICE 46 (1981) (confirming the use of earnings per share as by far the most widely used summary indicator of firm performance or risk).
where \( F(E_{it}) \) is the forecasted \( (F) \) quarterly earnings for firm \( i \) in quarter \( t \) \( (E_{it}) \) and \( \phi \) is an autoregressive parameter.\(^{59}\)

We do not estimate the autoregressive parameter \( \phi \) separately for each firm because this would add the requirement for long series of earnings data to be available for each firm in our sample. If firms with short earnings histories are less efficiently priced in financial markets, such a data requirement will eliminate those firms from our sample. To estimate unexpected earnings, we use a \( \phi = 0.22 \), a parameter which cross-sectionally minimizes the squared unexpected earnings in our sample.\(^{60}\) Given an expression for expected earnings (Equation 1), we proceed by estimating a scaled measure of unexpected earnings \( \text{(UE}_{it}) \) for each firm-quarter observation:

\[
\text{UE}_{it} = [E_{it} - F(E_{it})] / (P_{it} * S_{it})
\]

where, \( P_{it} \) is the beginning-of-quarter price, and \( S_{it} \) is the beginning-of-quarter number of shares outstanding. We scale our unexpected earnings \( \text{(UE}_{it}) \) measure by the beginning-of-quarter market value of equity to provide comparability across firms.

While there are alternative ways to estimate unexpected earnings,\(^{61}\) recent work suggests that our definition (Equation 1 and Equation 2 above) is a valid approximation of the way investors interpret earnings announcements.\(^{62}\) It is also reported that a quarterly time-series model defined similarly to Equation (1) performs better than analysts’ forecasts in predicting abnormal returns.\(^{63}\) Since we are concerned with investors’ reaction to information contained in an earnings announcement, our quarterly differences model appears to be a reasonable candidate. We also replicate our tests with expected earnings defined as analysts’ consensus forecasts, rather than the time-series model (1).

We measure abnormal stock returns using a simple mean market return adjustment:

\[
\text{AR}_{it} = \frac{1}{t} \sum_{\tau=2}^{t} (R_{it} - R_{mt})
\]

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60. To select an appropriate \( \phi \) parameter, we estimated a cross-sectional regression of differenced quarterly earnings on a one quarter lag of the same variable. The estimated cross-sectional \( \phi \) parameters ranged from 0.15 to 0.30. The pooled cross-sectional \( \phi \) parameter was 0.22.

61. See Brown et al., supra note 57. Later in this paper, we consider the use of analyst forecasts as well as the time-series model discussed here.

62. Jeffrey S. Abbarbanell & Victor L. Bernard, Tests of Analysts’ Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior, 47 J. FIN. 1181, 1183-85 (1992) (suggesting that investors may react improperly to earnings by incorrectly assuming earnings behave as a naive, seasonal random walk and recommending adjustment of the naive model for autocorrelation in earnings changes, in a manner similar to the model used in this paper, to improve the earnings forecast and better measure the overall amount of investor surprise to an earnings announcement).

63. Patricia C. O’Brien, Analysts’ Forecasts as Earnings Expectations, 10 J. ACCT. & ECON. 53, 80-81 (1988) (examining three composite analyst forecasts of earnings per share as proxies for expected earnings, presenting results which indicate that some time-series models may forecast better than financial analysts in predicting abnormal stock returns).
where, $AR_n$ is the abnormal return for firm $i$ for the five days centered around quarter $t$ earnings announcement date, $R_n$ is the stock return on day $t$, and $R_{nt}$ is the return on an equally-weighted market index of all NASDAQ stocks. We define the announcement day, $t = 0$, as the day on which the earnings figure is publicly released. To account for the possibility of earnings leaks or delayed responses to earnings announcements, we cumulate abnormal returns from $t = -2$ to $t = +2$. Having developed our measure of unexpected earnings ($UE_n$) and abnormal returns ($AR_n$), we are now able to define our measure of market efficiency.

C. Efficient and Inefficient Stocks

For each year, from 1984-1990, we partition the sample of firm-quarter observations into quintiles independently on the basis of unexpected earnings and abnormal returns. This yields twenty-five groups of stocks. We define an earnings announcement as “inefficient” if it falls in one of the two extreme unexpected earnings quintiles and the median abnormal return quintile. Thus, we define as inefficient the stocks that had very large unexpected earnings components (either positive or negative), yet did not experience a significant price adjustment on announcement. For these stocks, we revise our prior belief that they are efficiently traded. Our measure is admittedly noisy in that we use a zero-one classification scheme (each stock classified as efficient or inefficient), but this should only bias the tests against finding any relation between the variables which we believe drive efficiency and our efficiency classifications.

Some would argue that firms with a large positive (negative) earnings surprise and a corresponding negative (positive) price reaction are not “efficiently” priced, since the price reaction is in the opposite direction of that predicted by the earnings surprise. The fact that there was a price reaction at the announcement of an information event suggests that investors are processing the information content of the earnings announcement. This observation motivates us to include these firms in our set of “efficiently” priced stocks. However, the inconsistency between the surprise and price directions might be due to our use in some cases of inappropriate earnings expectations. Accordingly, we re-estimated the results we present in Tables V and VI excluding those firms with large positive (negative) earnings surprise and a corresponding negative (positive) price reaction. The conclusions of our analysis are unaffected by this modification.

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64. This represents the date on which quarterly earnings per share is first publicly reported in the various news media (such as the Wall Street Journal or Dow Jones News Service). Dates were obtained from the COMPUSTAT quarterly file.
65. See supra Equation 2.
66. See supra Equation 3.
67. See infra Figure 1.
68. See infra the black squares in Figure 1.
69. Based on comments received when presenting an earlier version of this work at the National Meetings of the American Accounting Association, San Francisco, 1993.
To be classified as "inefficient," a firm must experience a large unexpected change in earnings. If certain firms are predisposed to having large unexpected earnings, this could bias our classification scheme. To mitigate this problem, we define firms as

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70. This classification scheme minimizes the possibility that a firm experienced no earnings surprise, and consequently market participants did not change the price of the stock because the earnings announcement was perfectly anticipated.
"efficient" if they experience both large unexpected earnings and abnormal returns. These firms fall outside the median quintile of abnormal returns.71 Thus, out of the total sample, we focus on firms with large unexpected earnings (both positive and negative).72 Within this subset, we compare firms which had a large price response to the unexpected earnings (the "efficient" subsample) with those that had no price response to unexpected earnings (the "inefficient" subsample). Leaving out from the analysis firms with relatively small unexpected earnings is intended to sharpen the distinction between efficient and inefficient firms.

It is possible that partitioning the sample on abnormal returns is merely a finer partition on earnings surprise. To investigate this possibility, we present the mean and median unexpected earnings for our "efficient" and "inefficient" subsamples in Table I. The data indicate that the "efficient" and "inefficient" firms have similar unexpected earnings: 0.089 vs. 0.089 (i.e., 8.9 percent of stock price), on average, for the top quintile; and -0.097 vs. -0.079 for the bottom quintile.73 However, the differences in abnormal returns, namely in investors' reaction to the earnings announcement, are very pronounced: 0.042 vs. 0.00 for the top quintile, and -0.026 vs. 0.00 for the bottom quintile. On one hand, our sample of "inefficient" firms is, in fact, characterized by no investor reaction to earnings announcements, despite the fact that these announcements were highly surprising.74 On the other hand, the "efficient" firms' sample is characterized by large unexpected earnings and pronounced abnormal returns, due to investor reaction.75

D. Measuring the Efficiency Drivers

Having developed a measure of the efficiency of the price of a firm's security, we next define variables representing the efficiency drivers outlined in Part II. Consistent with prior notation, $t$ is used to denote quarters and $\tau$ is used to denote days, where the current quarter is quarter $t = 0$ and the announcement day is day $\tau = 0$. All data are from the CRSP Daily NASDAQ file unless otherwise noted.

1. Volume ($V_{\tau}$)

We measure the average daily dollar volume of trading in each security as the mean of the log of one plus daily dollar volume from $\tau = -50, -10.$76 Daily dollar vol-

71. See infra gray squares in Figure 1.
72. See infra left and right column in Figure 1.
73. The differences in unexpected earnings between "efficient" and "inefficient" firms are even smaller at the median: 0.035 vs. 0.034 and -0.039 vs. -0.037.
74. For example, the firms classified as inefficient with positive (negative) earnings surprises experienced earnings 8.87% higher (7.89% lower) than expected, on average. See infra Table I (revealing the extent of the surprise).
75. For example, the firms classified as efficient with positive (negative) earnings surprises experienced abnormal returns of 4.20% (-2.58%) on average around the announcement date. See infra Table I (revealing the extent of the price reaction among the efficient sample).
ume is defined as the closing transaction price ($P_n$) multiplied by number of shares traded ($S_n$).

$$V_{it} = \sum_{t = -50}^{-10} \ln(1 + P_{it} \ast S_{it}) / 41$$

(4)

The use of this measure is advocated to reduce the problems of skewness associated with a definition of the variable based on shares traded alone ($S_n$).\textsuperscript{77}

\textbf{TABLE I}
Mean and Median Unexpected Earnings and Abnormal Returns for "Efficient" and "Inefficient" Subsamples for Bottom and Top Quintile of Unexpected Earnings: 1984 - 1990

A firm's quarterly earnings announcement is classified as "inefficient" if the unexpected earnings are in the extreme quintiles of unexpected earnings and the associated abnormal return is in the median quintile of abnormal returns. A firm's quarterly earnings announcement is classified as "efficient" if the unexpected earnings are in the extreme quintile of unexpected earnings and the associated abnormal returns is outside the median quintile of abnormal returns. There are 7281 and 7311 firm-quarters classified as "efficient" in the Bottom and Top Unexpected Earnings Quintiles, respectively. There are 1511 and 1576 firm quarters classified as "inefficient" in the Bottom and Top Unexpected Earnings Quintiles, respectively.

<table>
<thead>
<tr>
<th>Bottom Quintile of Unexpected Earnings</th>
<th>Top Quintile of Unexpected Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unexpected Earnings</td>
<td>Abnormal Returns</td>
</tr>
<tr>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td>A. Efficient Subsample</td>
<td>-0.0965</td>
</tr>
<tr>
<td>B. Inefficient Subsample</td>
<td>-0.0789</td>
</tr>
<tr>
<td>Difference (A - B)</td>
<td>-0.0176</td>
</tr>
<tr>
<td>Wilcoxon rank-sum statistic*</td>
<td>-2.7500</td>
</tr>
</tbody>
</table>

* Wilcoxon rank-sum statistic is a test for equivalence of median values between the two subsamples and is asymptotically normal.

\textsuperscript{77} Id. at 337 (explaining the use of logarithms when the variable is not normally distributed).
2. Market Makers (MMₜ)

All firms in our sample are listed on the National Market System (NASDAQ). We therefore use the number of registered market makers for the issue as of the day preceding the earnings announcement date. We recognize that the level of market maker activity can differ for a given stock and across different stocks.

3. Size (SZₜ)

We measure size (market capitalization) as the log of market value of common equity (price per share times shares outstanding) as of the day preceding the earnings announcement.

4. Bid-Ask Spread Percentage (BAₜ)

We define the bid-ask spread percentage as the difference between the closing ask and the closing bid price divided by the average of the closing bid and the closing ask prices. We use an average of the percentage bid-ask spread from τ = -50, -10.

5. Standard Deviation of Returns (σ(Rₜ))

We define the standard deviation of returns as the sample standard deviation of daily returns over the current quarter of return data, from τ = -50, -10. In calculating returns, we use the average of the closing bid and ask prices to mitigate problems of bid-ask bounce.

6. Price (Pₜ)

Price is measured as the closing price of the common stock as of the day preceding the earnings announcement.

7. Analyst Following (ANₜ)

Analyst following is measured as the number of analysts who make earnings forecasts (for the current quarter’s earnings, t = 0) during the 90 days of each fiscal quarter. We obtain analyst following from the Institutional Brokers Estimate System (I/B/E/S) data. I/B/E/S follows earnings estimates of over 5,000 analysts working for approximately 400 investment firms worldwide. Thus, though not exhaustive, the I/B/E/S data is likely representative of analyst following.

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78. NASDAQ listed securities are primarily National Market System securities.
79. Size is commonly measured in this way by academics. See, e.g., Bhardwaj & Brooks, supra note 46.
80. The last transaction of the day can take place at either the bid or ask price. Thus, when there is no change in the bid or ask price, closing prices appear to be volatile as they “bounce” between the bid and ask price.
8. Institutional Holdings \((N_{i}, P_{i})\)

We obtain data on institutional ownership from CDA Investment Technologies Spectrum 3 and Spectrum 4.\(^{81}\) For each firm, this source documents the number of institutions holding the firm's stock and the percentage of the firm's stock held by institutions. The data are compiled from all SEC Form 13(f) filings and are reported quarterly (March, June, September, and December) for each year. We compile data from December 1986 through December 1990.

We determine the institutional holding for a particular firm by matching the current fiscal quarter to the last reported institutional ownership data. For example, a firm with a quarter end in either March, April, or May of 1988 in our sample would have institutional ownership data from the March 1988 Spectrum 3 and Spectrum 4. We examine two institutional ownership variables—the number of institutions holding a firm’s stock \((N_{i})\) and the percentage of a firm’s stock held by institutions \((P_{i})\).

IV. FINDINGS: UNIVARIATE DESCRIPTIVE STATISTICS

We present in Table II descriptive statistics by year for each of the eight efficiency drivers described in the previous section, as well as unexpected earnings and abnormal returns. The mean value of unexpected earnings for the full sample is generally close to zero.\(^{82}\) This contrasts with the mean value for our large surprise subsamples—both efficient and inefficient firms—of approximately eight to nine percent.\(^{83}\) Volume appears to have peaked in 1986, declining thereafter. Similarly, the number of market makers peaked in 1986, though the subsequent decline is less noticeable. Average firm size (log of market value of equity) has remained fairly constant. The average spread of NASDAQ National Market System firms appears to have increased steadily during our sample period. Daily return volatility was high in 1987 and 1990 relative to the other years. There has also been a steady decline in the mean price of NASDAQ securities. Finally, the mean level of institutional ownership and analyst following appears to have increased steadily during 1986-1990.

In Table III, we present descriptive statistics for each of the efficiency drivers for the full sample, the efficient subsample, and the inefficient subsample. We are especially interested in any systematic differences between the efficient and inefficient subsamples. To test for differences in median values on each efficiency driver, we employ the Wilcoxon rank-sum test.\(^{84}\) Somewhat surprisingly, there is no difference between our two samples (efficient and inefficient) on firm size. However, the average size of both efficient and inefficient samples (9.84 and 9.81) are smaller than the average size of the full sample (10.50). The reason is that the efficient and inefficient firms

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81. CDA Investment Technologies, Inc., 1355 Piccard Drive, Rockville, MD 20850.
82. See infra Table II second column, labeled UEit.
83. See infra Table I column 2, the mean bottom quintile of unexpected earnings column 6, the mean top quintile of unexpected earnings. See also supra notes 74-75.
84. The Wilcoxon Rank-Sum test is a statistical test used to establish whether differences between the distribution of two samples are reliably different from zero. See ALEXANDER MOOD ET AL., INTRODUCTION TO THE THEORY OF STATISTICS 522 (1974).
were selected on the basis of large earnings surprise. Smaller firms tend to have larger surprises than large firms. Hence, our selection criteria apparently yielded firms with below average size. Still, within this group of firms, the fact that the efficient and inefficient firms have almost indistinguishable size, on average, is surprising. Consistent with the efficiency indicators used recently by the courts,\textsuperscript{85} the inefficient firms have lower mean trading volume, fewer market makers, lower analyst following, and lower institutional ownership (number and percentage) than efficient firms.

### TABLE II
Mean Values of Selected Sample Characteristics by Calendar Year: 1984-1990

<table>
<thead>
<tr>
<th>Year</th>
<th>UE(_{it})</th>
<th>AR(_{it})</th>
<th>V(_{it})</th>
<th>MM(_{it})</th>
<th>SZ(_{it})</th>
<th>BA(_{it})</th>
<th>(\sigma(R_{it}))</th>
<th>P(_{it})</th>
<th>AN(_{it})</th>
<th>NI(_{it})</th>
<th>PI(_{it})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>0.0008</td>
<td>0.0033</td>
<td>9.35</td>
<td>7.94</td>
<td>10.48</td>
<td>3.58</td>
<td>2.28</td>
<td>13.32</td>
<td>0.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1985</td>
<td>-0.0079</td>
<td>-0.0001</td>
<td>9.81</td>
<td>7.80</td>
<td>10.59</td>
<td>3.95</td>
<td>2.01</td>
<td>14.36</td>
<td>0.54</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1986</td>
<td>-0.0019</td>
<td>0.0020</td>
<td>10.15</td>
<td>8.86</td>
<td>10.66</td>
<td>4.28</td>
<td>2.27</td>
<td>14.14</td>
<td>0.15</td>
<td>11.35</td>
<td>12.47</td>
</tr>
<tr>
<td>1987</td>
<td>0.0013</td>
<td>0.0024</td>
<td>9.91</td>
<td>7.58</td>
<td>10.51</td>
<td>5.06</td>
<td>2.78</td>
<td>11.64</td>
<td>0.62</td>
<td>12.04</td>
<td>12.63</td>
</tr>
<tr>
<td>1988</td>
<td>0.0020</td>
<td>0.0032</td>
<td>9.20</td>
<td>7.22</td>
<td>10.44</td>
<td>5.39</td>
<td>2.18</td>
<td>10.55</td>
<td>0.82</td>
<td>14.23</td>
<td>14.19</td>
</tr>
<tr>
<td>1989</td>
<td>-0.0053</td>
<td>0.0020</td>
<td>9.51</td>
<td>7.44</td>
<td>10.50</td>
<td>4.92</td>
<td>2.23</td>
<td>11.16</td>
<td>1.00</td>
<td>16.87</td>
<td>16.28</td>
</tr>
<tr>
<td>1990</td>
<td>0.0169</td>
<td>0.0071</td>
<td>9.08</td>
<td>7.54</td>
<td>10.34</td>
<td>6.97</td>
<td>2.90</td>
<td>9.60</td>
<td>1.08</td>
<td>18.91</td>
<td>18.02</td>
</tr>
</tbody>
</table>

Mean values are calculated on all available data for each year. The number of observations on each variable ranges from a low of 1,293 (No. of Instit. and % of Instit. in 1986) to a high of 7,950 (Unexpected Earnings, UE\(_{it}\)) in 1990.

In contrast to our expectation, the inefficient subsample has lower percentage spreads, lower volatility, and higher prices than the efficient subsample. We believe these observations are likely a result of the data used. First, the observation of lower spreads for the inefficient subsample is likely a result of the lower volatility and higher prices for this sample. Several researchers have observed a strong relation between volatility, price, and spreads.\textsuperscript{86} Second, many NASDAQ securities register little or no

\textsuperscript{85} See supra notes 30 and 32.

\textsuperscript{86} See Hans R. Stoll, \textit{Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests}, 44 J. Fin. 115, 129-32 (1989) (presenting results on the relation between bid-ask spread and market characteristics such as price, volume, return variance, number of market makers, and other characteristics); George J. Benston & Robert L. Hagerman, \textit{Determinants of Bid-Ask Spreads in the Over-the-Counter Market}, 1 J. Fin. Econ. 353, 354-56 (1974) (discussing and presenting results on the determinants of bid-ask spreads in the over-the-counter market using variables such as price, number of shareholders, number of dealers, and unsys-
trading activity for several days or even weeks. Consequently, the measured volatility of these securities is lower than firms that are otherwise similar but trade more frequently. Finally, the higher stock price for the inefficient subsample is likely a result of return measurement biases. Transaction prices occur at either the bid or the ask price. Consequently, firms with larger spreads are more likely to have larger measured returns because of the potential bid-ask bounce—adjacent returns being measured at the bid and ask prices. This would lead us to observe lower-priced securities in our efficient subsample as they are more likely to experience larger measured returns because of their larger spreads. Although these biases are plausible explanations of the observed results, the question of whether spreads, volatility, and price level are indicators of efficiency is still to be examined.

### TABLE III


The significant difference in the median value of the number of Market Makers and number of Analysts results from the fact that the number of Market Makers and number of Analysts only take on integer values. Thus, though both samples have the same median value, a significant portion of the "Inefficient" subsample falls below this median value relative to the "Efficient" subsample.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th>&quot;Efficient&quot; Subsample</th>
<th>&quot;Inefficient&quot; Subsample</th>
<th>Difference &quot;Effic.&quot; - &quot;Ineffic.&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Obs.</td>
<td>Mean</td>
</tr>
<tr>
<td>Volume</td>
<td>9.55</td>
<td>10.03</td>
<td>48,456</td>
<td>8.73</td>
</tr>
<tr>
<td>Mkt. Makers</td>
<td>7.73</td>
<td>6.00</td>
<td>46,458</td>
<td>7.72</td>
</tr>
<tr>
<td>Size</td>
<td>10.50</td>
<td>10.40</td>
<td>48,348</td>
<td>9.84</td>
</tr>
<tr>
<td>Bid-ask Spread</td>
<td>5.06</td>
<td>3.54</td>
<td>37,670</td>
<td>6.97</td>
</tr>
<tr>
<td>Std. Dev. Ret.</td>
<td>2.41</td>
<td>2.05</td>
<td>37,418</td>
<td>2.96</td>
</tr>
<tr>
<td>Price</td>
<td>11.91</td>
<td>8.00</td>
<td>47,144</td>
<td>7.13</td>
</tr>
<tr>
<td>No. Analysts</td>
<td>0.68</td>
<td>0.00</td>
<td>49,349</td>
<td>0.39</td>
</tr>
<tr>
<td>No. Institutions</td>
<td>15.39</td>
<td>7.00</td>
<td>32,268</td>
<td>8.84</td>
</tr>
<tr>
<td>% Institutions</td>
<td>15.21</td>
<td>8.38</td>
<td>32,268</td>
<td>10.76</td>
</tr>
</tbody>
</table>

* Significant at the 1% level using a Wilcoxon rank-sum test.
While our results confirm some of the rules courts have applied,\textsuperscript{87} inferences from the preceding univariate analysis must be conditioned by the complex correlation structure between the variables used in the analysis. Table IV presents the Spearman correlation matrix for the variables considered.\textsuperscript{88} Many of the observed correlations exceed fifty percent while all but two are statistically significant at less than the five percent

\textbf{TABLE IV}

\textbf{Spearman Correlation Coefficients: 1984-1990}

The Spearman correlation coefficients are estimated on all available data from 1984 to 1990. The number of observations range from 24,432 (for the correlation between change in the number of institutions holding a firm's stock and the volatility of returns) to 48,456 (for the correlation between unexpected earnings and volume). All correlations are statistically significant at the 5 percent level unless otherwise noted.

<table>
<thead>
<tr>
<th>Variable</th>
<th>UE\textsubscript{it}</th>
<th>AR\textsubscript{it}</th>
<th>V\textsubscript{it}</th>
<th>MM\textsubscript{it}</th>
<th>SZ\textsubscript{it}</th>
<th>BA\textsubscript{it}</th>
<th>σ(\text{R})\textsubscript{it}</th>
<th>P\textsubscript{it}</th>
<th>AN\textsubscript{it}</th>
<th>N\textsubscript{it}</th>
<th>P\textsubscript{iit}</th>
</tr>
</thead>
<tbody>
<tr>
<td>UE\textsubscript{it}</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR\textsubscript{it}</td>
<td>0.230</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>V\textsubscript{it}</td>
<td>0.024</td>
<td>-0.023</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM\textsubscript{it}</td>
<td>0.003</td>
<td>0.548</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SZ\textsubscript{it}</td>
<td>0.049</td>
<td>0.789</td>
<td>0.321</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BA\textsubscript{it}</td>
<td>0.076</td>
<td>0.232</td>
<td>-0.833</td>
<td>-0.433</td>
<td>-0.824</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>σ(\text{R})\textsubscript{it}</td>
<td>0.050</td>
<td>-0.015</td>
<td>0.074</td>
<td>0.170</td>
<td>-0.261</td>
<td>0.274</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P\textsubscript{it}</td>
<td>0.078</td>
<td>0.039</td>
<td>0.512</td>
<td>0.032</td>
<td>0.784</td>
<td>-0.714</td>
<td>-0.453</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AN\textsubscript{it}</td>
<td>-0.008</td>
<td>-0.002</td>
<td>0.478</td>
<td>0.222</td>
<td>0.481</td>
<td>-0.418</td>
<td>-0.041</td>
<td>0.355</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N\textsubscript{it}</td>
<td>0.011</td>
<td>0.013</td>
<td>0.538</td>
<td>0.254</td>
<td>0.646</td>
<td>-0.531</td>
<td>-0.175</td>
<td>0.552</td>
<td>0.509</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>P\textsubscript{iit}</td>
<td>0.016</td>
<td>0.017</td>
<td>0.442</td>
<td>0.186</td>
<td>0.549</td>
<td>-0.420</td>
<td>-0.165</td>
<td>0.513</td>
<td>0.465</td>
<td>0.944</td>
<td>1.000</td>
</tr>
</tbody>
</table>

* Not significant at the 5 percent level.

\textsuperscript{87} For example, the \textit{Cammer} court suggested volume and analyst following, variables that we find to be important indicators of efficiency in our study. But, the same court advocated the use of the number of market makers, a variable that we find unimportant as an indicator of efficiency. \textit{See Cammer}, 711 F. Supp. at 1285.

\textsuperscript{88} A Spearman correlation matrix summarizes the pairwise correlations among a set of variables. \textit{See} MOOD ET AL., \textit{supra} note 84, at 155. For example, the Spearman correlation between the pair of variables UE\textsubscript{p} and AR\textsubscript{p} is 23%.
level. This demonstrates the hazards of the courts’ current use of various efficiency indicators, as if the indicators are independent and each one individually contributes to efficiency.

V. FINDINGS: MULTIVARIATE ANALYSIS

In order to determine the incremental contribution of each variable to the probability of classifying a firm as inefficient using the previously discussed drivers, we use a multivariate logit model. A logit model is analogous to a linear regression model except the dependent variable assumes discrete values. We employ a binary logit model in which the dependent variable ($I_u$) takes on one of two values: a value of 1 if an earnings announcement is classified as inefficient and a value of zero otherwise. We estimate the following logit model:

$$I_u = a + b_1V_u + b_2MM_u + b_3SZ_u + b_4BA_u + b_5\sigma(R_u) + b_6P_u + b_7AN_u + b_8NI_u + e_u$$

(5)

where each of the explanatory variables is as defined in Part III. The logit model is estimated separately for each year, for the 1987-90 period in which we have institutional ownership data, and for the 1984-90 period. We present the results of this analysis in Table V.

The main finding of the logit analysis is that volume of trade and number of analysts following a stock yield results consistent with our expectations and the use by courts of these variables as indicators of the efficiency with which a firm’s securities are priced. Specifically, securities with low volume and fewer analysts are more likely to be traded inefficiently.

89. Statistical significance is a term used in econometrics that describes the confidence with which a researcher can conclude a certain hypothesis can be rejected. For example, in the context of our study, the observed correlations between volume and size is sufficiently different from zero to allow use to conclude there is a positive correlation between volume and size. For a thorough discussion, see G. S. MADDALA, ECONOMETRICS 45-46 (1977).

90. A multivariate logit model estimates the effect that several explanatory variables have on the probability of a certain outcome. In our analysis, we are estimating the effect of various indicators of efficiency have on the probability that a firm is classified as efficient or inefficient. See G. MADDALA, LIMITED-DEPENDENT AND QUALITATIVE VARIABLES IN ECONOMETRICS 22 (1983).

91. See G. MADDALA, supra note 90 (discussing logit models extensively).

92. Models estimated using the percentage of institutional ownership in lieu of the number of institutions yielded similar results to those reported.

93. To test the robustness of these results, we estimate the logit model for the positive and negative earnings surprises separately. The general results are the same for both subsamples. We also modify our efficiency classification by excluding firms in the second and fourth quintiles of abnormal returns from our efficient firms. Again, the general results are unaffected.

94. For example, for the 1984-1990 sample period, Table V shows the logit coefficients on volume of trading, $V_u$, and number of analysts, $AN_u$, as -0.097 and -0.073, respectively, both significant at less than one percent. See infra Table V.

95. The coefficients are negative because an efficient stock is coded as zero in the logit analysis. The more analysts, for example, the more likely a security is to be traded efficiently.
TABLE V
Logit Models of Efficiency: 1984 - 1990

Coefficient estimates represent each variables impact on the probability of being classified as “inefficient.” Logit models are estimated on firms which had unexpected earnings in the top or bottom quintile of the distribution of unexpected earnings for the calendar year. Firms which had a small price response to these large unexpected earnings were classified as “inefficient” (dependent variable takes on a value of 1). A small price response was defined as the middle quintile of price response (mean market-adjusted return) to quarterly earnings announcements for all firms in the calendar year. Approximately 15 percent of quarterly earnings announcement with a large unexpected component are defined as “inefficient” using this classification scheme. All statistical tests on coefficient estimates are one-tailed. The null hypothesis of $H_0$: $\beta_i = 0$ is tested versus the alternative hypothesis of $H_a$: $\beta_i > 0$ for Bid-ask Spread and standard deviation of return, $\sigma(R_i)$. The null hypothesis of $H_0$: $\beta_i = 0$ is tested versus the alternative hypothesis of $H_a$: $\beta_i < 0$ for Volume, Market Makers, Size, Price, No. of Analysts, and No. of Institutions. All models are statistically significant at conventional significance levels using a $\chi^2$ test statistic.

<table>
<thead>
<tr>
<th>Estimation period</th>
<th>Intercept</th>
<th>Volume</th>
<th>Market Makers</th>
<th>Size</th>
<th>Bid-ask Spread</th>
<th>Std. dev.</th>
<th>Price</th>
<th>No. of Analysis</th>
<th>No.of Instit.</th>
<th>No. of Observ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{it}$</td>
<td>$V_{it}$</td>
<td>$MM_{it}$</td>
<td>$SZ_{it}$</td>
<td>$BA_{it}$</td>
<td>$\sigma(R_{it})$</td>
<td>$P_{it}$</td>
<td>$AN_{it}$</td>
<td>$NI_{it}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1984</td>
<td>-1.359</td>
<td>-0.091</td>
<td>-0.034</td>
<td>0.118</td>
<td>-0.106</td>
<td>-0.039</td>
<td>0.017</td>
<td>-0.198</td>
<td>-</td>
<td>752</td>
</tr>
<tr>
<td>1985</td>
<td>-1.764*</td>
<td>0.034</td>
<td>0.026</td>
<td>-0.033</td>
<td>-0.004</td>
<td>-0.148</td>
<td>0.028</td>
<td>-0.123*</td>
<td>-</td>
<td>1,365</td>
</tr>
<tr>
<td>1986</td>
<td>-0.339</td>
<td>-0.111*</td>
<td>-0.010</td>
<td>0.025</td>
<td>-0.112</td>
<td>-0.024</td>
<td>0.016</td>
<td>-0.239*</td>
<td>-</td>
<td>1,808</td>
</tr>
<tr>
<td>1987</td>
<td>-4.395*</td>
<td>-0.063*</td>
<td>0.007</td>
<td>0.342</td>
<td>0.020</td>
<td>-0.084</td>
<td>-0.002</td>
<td>0.029</td>
<td>-0.002</td>
<td>2,077</td>
</tr>
<tr>
<td>1988</td>
<td>-1.211</td>
<td>-0.075*</td>
<td>-0.013</td>
<td>0.037</td>
<td>-0.035</td>
<td>-0.068</td>
<td>0.027</td>
<td>-0.026</td>
<td>0.001</td>
<td>2,052</td>
</tr>
<tr>
<td>1989</td>
<td>-5.177*</td>
<td>-0.126*</td>
<td>-0.003</td>
<td>0.479</td>
<td>-0.024</td>
<td>-0.008</td>
<td>-0.001</td>
<td>-0.150*</td>
<td>0.001</td>
<td>2,036</td>
</tr>
<tr>
<td>1990</td>
<td>-2.097*</td>
<td>-0.185*</td>
<td>0.016</td>
<td>0.205</td>
<td>-0.044</td>
<td>0.022</td>
<td>0.026</td>
<td>-0.094*</td>
<td>-0.003</td>
<td>1,999</td>
</tr>
<tr>
<td>1984-90</td>
<td>-2.846*</td>
<td>-0.097*</td>
<td>-0.001</td>
<td>0.220</td>
<td>-0.025</td>
<td>-0.040</td>
<td>0.012</td>
<td>-0.073</td>
<td>-</td>
<td>12,089</td>
</tr>
<tr>
<td>1987-90</td>
<td>-3.416*</td>
<td>-0.119*</td>
<td>0.002</td>
<td>0.293</td>
<td>-0.024</td>
<td>-0.027</td>
<td>0.009</td>
<td>-0.072*</td>
<td>0.000</td>
<td>8,593</td>
</tr>
</tbody>
</table>

* Significant at the 1% level, one-tailed test.
† Significant at the 5% level, one-tailed test.
^ Significant at the 10% level, one-tailed test.
Second, we find that two variables, which yield statistically significant differences between the efficient and inefficient subsamples in the univariate analysis, are no longer statistically significant in the multivariate analysis: the number of market makers and the number of institutions holding a firm’s stock.\textsuperscript{96} That is, once the multivariate analysis accounts for the correlation between efficiency drivers, the number of market makers and institutional holdings do not marginally contribute to distinguishing efficient from inefficient firms.

The evidence on the insignificance of the number of market makers in distinguishing between efficient and inefficient firms is particularly important, given the frequent use of this variable by courts as an efficiency indicator.\textsuperscript{97} Apparently, market makers just “make a market” in the stock, namely match buy and sell orders, without contributing to the information available about the stock. The Brady Commission report on the October, 1987, market crash noted “[i]t is not unusual for these large national full-service firms and wholesalers to make markets in more than 1,000 different securities.”\textsuperscript{98} It is therefore not surprising that in contrast to analysts, market makers generally do not analyze and disseminate information about the stock that they make a market for and therefore do not contribute to the efficiency of the stock’s price.

Third, four variables (size, percentage spread, volatility, and price) yield results which run counter to intuition and the use of these variables by the courts as indicators of market efficiency.\textsuperscript{99} These results may be due to statistical factors, such as the substantial correlation (multicollinearity) between these variables and others used in the analysis (e.g., size and volume). But there also might be substantive reasons for the failure of these variables to indicate efficiency.\textsuperscript{100} In any case, our results suggest that courts should exercise caution in the use of these four variables as indicators of the efficiency with which a firm’s securities are priced.

VI. ANALYSTS’ FORECASTS

Our measure of the earnings surprise, and the consequent efficiency/inefficiency classification, is based on the change in quarterly earnings.\textsuperscript{101} One can argue that this measure does not fully capture the most updated investor expectations of earnings, and, hence, potentially misspecifies the earnings surprise. To overcome this objection, we measure the earnings surprise relative to consensus analysts’ forecasts, which reflect on

\textsuperscript{96} For example, for the 1987-1990 sample period, Table V shows the logit coefficients on number of market makers, MM, and number of institutions, NI, respectively, as 0.001 and less than 0.001, both insignificant at less than 10 percent. See infra Table V.

\textsuperscript{97} See, e.g., Cammer, 411 F. Supp. 1264, part II.


\textsuperscript{99} For example, for the 1987-1990 sample period, Table V shows the logit coefficients on size, SZ, percentage spread, BA, volatility, \( \sigma(R) \), and price, \( P \), respectively, as 0.293, -0.024, -0.027, and 0.009. See infra Table V.

\textsuperscript{100} For example, the size of a firm may be unrelated to the efficiency with which the market prices the firm’s stock. Size might merely serve as a proxy for the true indicators of efficiency.

\textsuperscript{101} See supra part III, Equations 1 and 2.
a timely basis investor expectations. Analysts have at their disposal broad information sources, and their forecasts are available to the investing public. Investor expectation should, therefore, parallel analysts' forecasts. Furthermore, analysts' forecasts are more timely than time series models.

To test the robustness of our results, we incorporate analysts' forecasts in lieu of the quarterly time series model. Unexpected earnings ($U_{Es}$) are measured by the difference between actual earnings per share ($EPS_{t}$) and analysts' forecasts of earnings per share ($AF_{t}$) scaled by beginning of period price ($P_{t-1}$):

$$UE_{Es} = (EPS_{t} - AF_{t}) / P_{t-1}$$  \hspace{1cm} (6)

We use the I/B/E/S mean (consensus) analysts' forecasts during the last thirty days of the fiscal quarter under consideration.

We proceed by estimating two additional logit models. In the first model, earnings announcements are classified as efficient or inefficient with respect to unexpected earnings for the subset of firms that have at least one analyst's forecast. A logit model is then estimated on this subset of firms (4,592 firms from 1984-1990). The results of this analysis are reported in panel B of Table VI (for ease of comparison, panel A contains the full sample results based on the time series model previously reported).

In the second model, we use analysts' forecasts to estimate expected earnings when forecasts are available, and the time series model (Equation 1) when forecasts are unavailable. Earnings announcements are then classified as efficient or inefficient with respect to expected earnings based on the union of the time series model and analysts' forecasts estimates of expected earnings. The results of this analysis are presented in panel C of Table VI.

The results reported in Table VI demonstrate that our findings are robust to the earning expectation model used (time-series or analysts). Firms with low volume and fewer analysts remain more likely to be classified as inefficient, consistent with the hypothesis that these variables are efficiency drivers. Number of market makers and number of institutional investors are insignificant indicators of market efficiency, even in the efficiency/inefficiency classification based on analysts' forecasts. Firm size, percentage spread, volatility and price remain significant, but in the opposite sign to that predicted.

102. See O'Brien, supra note 63.
103. BROWN ET AL., supra note 30, at 20.
104. See O'Brien, supra note 63 (discussing the use of analyst forecasts in lieu of time-series models to estimate expected earnings).
105. For example, for the 1984-1990 sample period, Table VI, panel C, shows significant logit coefficients on volume of trading, $V_n = -0.100$, and number of analysts, $AN_n = -0.0437$. On the other hand, the coefficients on the other variables, $MM_n$, $SZ_n$, $BA_{n}$, $\sigma(R_n)$, $P_n$, and $NL_n$, are either insignificant or exhibit a sign opposite to predictions. See supra part IV.
TABLE VI
Logit Models of Efficiency Incorporating Analysts' Forecasts: 1984 - 1990

Coefficient estimates represent each variables impact on the probability of being classified as "inefficient" (Table V). Panel A represents results when classification is based on expected earnings estimated from time series model. Panel B represents results when classification is based on expected earnings from analyst forecasts and models are estimated only for firms with analyst forecasts. Panel C represents results when classification is based on expected earnings based on analyst forecasts when available and time series model when analyst forecasts are unavailable.

<table>
<thead>
<tr>
<th>Estimation period</th>
<th>Intercept</th>
<th>Volume Maker</th>
<th>Market Size</th>
<th>Bid-ask Spread</th>
<th>Std. dev. Price</th>
<th>No. of Analysts</th>
<th>No. of Instit.</th>
<th>No. of Observ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_{it} )</td>
<td>( V_{it} )</td>
<td>( MM_{it} )</td>
<td>( SZ_{it} )</td>
<td>( B_{it} )</td>
<td>( \sigma(R_{it}) )</td>
<td>( P_{it} )</td>
<td>( AN_{it} )</td>
<td>( NI_{it} )</td>
</tr>
</tbody>
</table>

Panel A: Models based on Time-Series Estimates of Expected Earnings

1984-90: -2.846* -0.097* -0.001 0.220 -0.025 -0.040 0.012 -0.073* 0.000 12,089
1987-90: -3.416* -0.119* 0.002 0.293 -0.024 -0.027 0.009 -0.072* 0.000 8,593

Panel B: Models based on Analyst Forecasts of Expected Earnings

1984-90: -2.500* -0.109* 0.013 0.196 -0.016 -0.078 0.012 -0.048* 0.000 4,592
1987-90: -2.429* -0.115* 0.002 0.187 -0.012 -0.079 0.019 -0.038* -0.003 3,824

Panel C: Models based on Time-Series Estimates and Analyst Forecasts of Expected Earnings

1984-90: -2.758* -0.100* -0.005 0.221 -0.026 -0.043 0.009 -0.044* 0.000 11,891
1987-90: -3.388* -0.118* -0.001 0.298 -0.024 -0.033 0.007 -0.050* -0.003 8,445

* Significant at the 1% level, one-tailed test.
† Significant at the 5% level, one-tailed test.
^ Significant at the 10% level, one-tailed test.
VII. CONCLUSION

Subsequent to the Supreme Court decision in Basic, Inc. v. Levinson,106 lower courts began implementing the fraud-on-the-market theory.107 A key element in such an implementation is the assumption that the security is traded in an efficient market during the class period.108 The courts’ determination of efficiency has to date been based on intuition, rules of thumb, or both.109

This study attempts to substitute empirical evidence for such intuition. We classify a large sample of NASDAQ companies into subsamples of efficient and inefficient firms, based on investors’ reaction to surprising earnings announcements. We then test econometrically the ability of a set of candidate efficiency drivers to systematically discriminate between the efficient and inefficient stocks. We do this in a multivariate framework which accounts for the significant correlations among most proposed efficiency drivers.

Our findings, based on two models of expected earnings—time-series and analysts’ forecasts—clearly indicate two factors as efficiency drivers: volume of trade and number of analysts following the stock.110 The other variables examined—firm size, percentage bid-ask spread, return volatility, price, and institutional holdings—either fail the significance test or yield results counter to our expectations.111

In the appendix, we present descriptive data for the calendar year 1990 for analyst following and volume of trade. In 1990, sixty-three percent of NASDAQ firms had no analyst following (as measured by I/B/E/S).112 In the same year, seventy-five percent of firms had mean volume113 in excess of 6.49.114 Thus, a stock with at least one analyst and volume in excess of 6.49 would, on average, be presumed efficient with respect to the information contained in earnings.115 Stronger efficiency presumptions

108. See supra note 107.
109. See Robinson, supra note 39 (discussing the variables used by the courts to determine efficiency).
110. See infra Tables V and VI (supporting these statements). See generally VICTOR L. BERNARD, CHRISTINE BOTOSAN, & GREGORY D. PHILLIPS, CHALLENGES TO THE EFFICIENT MARKETS HYPOTHESIS: LIMITS TO THE APPLICABILITY OF FRAUD-ON-THE-MARKET THEORY (University of Michigan Graduate School of Business Working Paper, February, 1994) (suggesting volume is an efficiency driver).
111. See infra Tables V and VI (supporting these statements).
112. Based on analyst forecast data obtained from the Institutional Brokers Estimate System, Lynch, Jones & Ryan, 345 Hudson St., N.Y., N.Y. 10014.
113. We measure volume using Equation 4 for econometric purposes. See the appendix for a discussion of how this measure translates to a more intuitive measure.
114. Based on volume data obtained from the Center for Research in Security Prices, University of Chicago, Graduate School of Business, Chicago, Ill.
115. This statement is based on the results presented in Tables V and VI that show a statistically signifi-
could be based on higher levels of these indicators (e.g., two or more analysts following the stock).\textsuperscript{116}

Our findings are attractive in their parsimony. They suggest that out of a multitude of possible efficiency indicators, courts should look closely at just two key variables in considering the market efficiency presumption underlying the fraud-on-the-market theory.

\textsuperscript{116} Increasing analyst following or volume, according to our analysis, reduces the probability that a firm's stock would be classified as inefficient.
Appendix

In this appendix, we present descriptive statistics on the number of analysts and volume. The statistics presented in the appendix are based on 7,950 quarterly earnings announcements by NASDAQ firms during 1990. Volume data are available for 7,880 of these quarterly earnings announcements. If I/B/E/S reports no analyst following for a particular quarterly earnings announcement, we assume there is no analyst following. These statistics are intended to provide legal practitioners with guidance in the comparison of defendant firms to the population of NASDAQ firms.

Volume ($V_n$) is measured as the mean of the log of one plus dollar volume (closing price per share times shares traded, see equation 4). To translate this number to a more intuitive measure, use the following transformation:

$$V'_n = e^{V_n}.$$

The result of this transformation ($V'_n$) approximates the mean daily dollar volume. This approximation is exact if daily dollar volume is constant over the period for which the mean is calculated. If daily dollar volume varies considerably from day to day then this approximation will not be appropriate. Assuming this approximation is accurate, mean daily dollar volume for the median NASDAQ firm in 1990 was $e^{53} = \$13,767$.

Analyst following is the number of I/B/E/S analysts making earnings forecasts for a firm during a fiscal quarter.

### Distribution of Analyst Following and Volume for NASDAQ Firms: 1990

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<thead>
<tr>
<th>Percentile</th>
<th>Volume</th>
<th>Analyst Following</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.01</td>
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</tr>
<tr>
<td>5</td>
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<td>0</td>
</tr>
<tr>
<td>10</td>
<td>3.69</td>
<td>0</td>
</tr>
<tr>
<td>25</td>
<td>6.49</td>
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<tr>
<td>50(median)</td>
<td>9.53</td>
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<tr>
<td>75</td>
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</tr>
<tr>
<td>90</td>
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<td>5</td>
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<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>volume</td>
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<tr>
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