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Test of Market Efficiencies Using Experimental Electronic Markets

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The overall efficient market hypotheses (EMH) has been divided into three categories: (1) weak form EMH, (2) semi-strong form EMH, and (3) strong form EMH. Numerous researchers have used empirical data to test these hypotheses. Results have varied greatly. Some concluded that market prices reflect all available information, public and private, and therefore strong form efficient conditions are met. Others, however, drew opposite conclusions. Lack of control in field studies may have been a key contributing factor to the conflicting results. The purpose of this study is to take advantage of the recent technological advances and provide a controlled environment for performing investigations of market trader behavior and market efficiency. Results of this research show a positive relationship between information quality and trading profits in a market, evidence supporting semi-strong form EMH. J BUSN RES 1998. 41.145–151. *© 1998 Elsevier Science Inc.*

The strong form of the efficient market hypothesis (EMH) predicts that no traders have higher expected profits, a prediction based on the assumption that both public and private information are fully reflected in the market prices. Semi-strong form EMH, however, assumes that the market prices reflect only publicly revealed information. Under the semi-strong form, traders with only publicly revealed information should not be able to derive above average profits from their trading. Insiders in the market could, due to the possession of private (non-public) information, earn abnormal profits.

The weak form EMH states that current stock prices reflect historical sequence of prices, price changes, trading volume, and other historical market information. It implies that any trading rule that uses past market data to predict future returns would not be of value.

One possible test of these market hypotheses is to study market insiders' profits. Numerous prior researchers (Baesel and Stein, 1979; Eyssell, 1990, 1991; Finnerty, 1976; Givoly and Palmon, 1985; Jaffe, 1974; Keown and Pinkerton, 1981; Nunn, Madden, and Gombola, 1983; Penman, 1982; Raad and Wu, 1995; Seyhun, 1986; Syed, Liu, and Smith, 1989) have done significant work in this respect. Researchers have collected transaction data from such sources as *Official Summary of Security Transactions and Holdings, Stock Price Tape of the Center for Research in Security Prices* (CRSP) of the University of Chicago, or *Insiders' Chronicle.* Based on the empirical data, researchers compared average profits of all traders to the profits of registered insiders during selected periods. From those observations, researchers attempted to identify inside information value in terms of insider trading performance relative to general market performance. In such *ex post* research, it is difficult to determine what factors actually contribute to insiders' obtaining abnormal gains, to identify the nature and quality level of inside information, and to precisely determine what traders were linked directly or indirectly to inside information. For example, board members (SEC insiders) may actually be inactive while their families or close friends are "tipees" and extensive market traders.

To overcome limitations relating to the nature of available empirical data, our approach to the study of market efficiency issues involves the development and utilization of controlled laboratory experiments. We set up an electronic stock trading market and use this structure to perform a series of controlled laboratory experiments. By carefully controlling factors that affect the operation and outcomes of the market, we study the impact of various forms of inside information availability on the profits of traders. Based on the findings regarding insiders' profits, we are able to study the market efficiency hypotheses.

Experimental Design

To conduct the desired research investigation, we developed an electronic market shell incorporating stock market trading

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activities and subsequent stock price adjustments based on transactions and random shocks. The shell was constructed to provide an electronic process for passing messages, collecting information, performing direct calculations, and integrating random components with direct numerical computations to determine market changes in stock price, individual participant profits, and overall market performance.

Under this shell, a server machine plays the control role (the SEC in the real security market) while others are market participants (stock traders). The server (or monitor) is responsible for registering traders in the market, announcing the opening or ending of a trading period, monitoring the market at a pre-assigned frequency, and stopping the market at any time if necessary. Trader machines provide an interface to the human subjects for performing market activities in the experimental stock market.

The shell allows the number of stocks (from one to six) to be chosen when an experiment is initiated. Stocks are typically named using three repeated letters, for example, AAA, BBB, CCC, DDD, EEE, and FFF. At the time of initiation of an experiment, share prices are set for each stock. A specific amount of cash and stocks are endowed to every trader at the beginning of an experiment.

The electronic market trader interface provides instructions on keystrokes to perform specific market activities or invoke support functions during an experimental period. By correctly following instructions, subjects can purchase or sell stocks and can review previous histories of stock prices, personal transactions, market transactions, and market indices.

The interface also provides traders with information relating to the stock issuing companies' prospects. There are two types of information: public and private. Public information is shown continuously in the information area, providing information every period throughout the experiment. This information is common to all the traders. For private information, however, the F9 key has to be pressed for access. A trader can only access and display such information for the companies (stocks) for which the trader is an insider. When the F9 key is pressed and insider information is shown, the trader is considered in "insider active status." A monetary penalty is imposed if a trader is caught in "insider active status" by the monitor. The monitor electronically checks the market at a random (pre-determined expected) frequency to check the status of traders. A trader can stop active access of the private information by pressing the ESC key. The insider information disappears once the ESC key is pressed and the trader is no longer in "insider active status." Thus, if a trader can get in and out of insider active status without monitor surveillance having occurred, the individual escapes detection and penalty. As the expected rate of monitoring increases, the likelihood of accessing inside information without being discovered and penalized diminishes.

Private information is not necessarily of the same quality or reliability. In our experiments, we used two quality levels for inside information. We use the symbol "I" to refer to information with higher reliability and "II" to information with lower reliability. Both types of inside information possess greater reliability than public information which we denote using the symbol "X." That is:

$$R(\text{Public}) < R(\text{"I"}) < R(\text{"II"})$$

where R(Public) is the reliability of public information; R("I") is the reliability of type "I" private information; and R("II") is the reliability of type "II" private information.

The different types of information signals were generated as follows:

Type I: random draws from normal distribution centered at true information signal and having a variance of 0.0279;
Type II: random draws from normal distribution centered at true information signal and having a variance of 0.0534;
Type X: random draws from uniform distribution centered at true information signal and having a variance of 0.0835.

At the end of a period, new prices of stocks are calculated and a summary of that period's transactions and other relevant market information automatically pops up. After an appropriate length of time for traders to read the summary, the monitor announces the commencement of another period, and traders begin with an updated portfolio resulting from the previous one. The market continues in the same way until the end of a predetermined number of experimental periods.

The experiments utilize the induced-value approach pioneered by Vernon Smith (1976, 1988). Smith emphasized the use of a reward structure incorporating sufficient monetary value to drive the experiments by motivating subjects' performance. He argued that well designed laboratory experiments, which parallel the salient features of real world markets, can offer significant implications for theory development and testing. Following Smith, we used a monetary incentive structure in all of our experiments. In all experiments, the payout to participants is directly related to the experimental profits individual subjects attain in the competitive experimental market structure.

Methodology

As part of our analysis, we consider the market model in financial theory used by prior researchers in the securities market. Suggested by Fama et al. (1969), the market model studies the relationship between the performances of a specific stock and the whole market. In a stock market, a given stock's price will tend to rise or decline somewhat more or somewhat less than the market as a whole. Fama et al. (1969) characterized this relationship using the following model of stock returns and market returns:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_t$$

where R_{it} = the rate of return on security i during period t
α_i = the intercept or constant for security i in the regression
β_i = the slope coefficient for security i
R_{mt} = the rate of return on a market index during period t
ϵ_t = a random error with expected value of zero during period t.

From the above model, the expected rate of return for security i during period t should be:

$$E(R_{it}) = E(\alpha_i) + E(\beta_i R_{mt}) + E(\epsilon_t) = \alpha_i + \beta_i R_{mt}$$

since $E(\epsilon_t)$ is zero. The abnormal return for security i in period t would be equal to the actual return minus the expected return:

$$R_{it} - E(R_{it}) = R_{it} - (\alpha_i + \beta_i R_{mt}).$$

The key point of this model is that in the long run, these abnormal returns should sum to zero. That is, a trader is expected to experience no abnormal returns for any stock over a long period. We sought to study the impacts of various control factors on the abnormal returns that a subject might earn. If a trader is able to tell when a stock is having positive or negative abnormal returns and can make use of his/her predictions, he/she can outperform the market.

In our experiments, each trader's activities and all market activities and changes are automatically saved for all periods, enabling us to perform necessary analyses. Two coefficients, α and β, have to be calculated using historical data for the market model. Since there are 40 periods in each of our experiments, we used the first half (20) as the set of historical periods for estimating the αs and βs in the regression model. The last 20 periods were used in the abnormal profits analyses. For example, in a particular experiment, α_I and β_I are calculated using both stock I's and the market's rates of return from the first 20 periods. Stock i's rate of return in period t is defined as:

$$R_{it} = (p_{i,t} - p_{i,t-1})/P_{i,t-1}$$

where $p_{i,t}$ is the price of stock i at period t. The market index used in our experiments is price based with rate of return calculated as:

$$R_{mt} = (AVG_t - AVG_{t-1})/AVG_{t-1}$$

where AVG_t is the equally weighted average stock prices at period t with AVG_0 referring to the initial average prices.

As explained above, we utilized a three-level information hierarchy to enable us to study the relationships between insider information and trading profits and the relationships between information quality and trading profits. We structured the specific information hierarchy (presence of type I, type II, and type X information) for each experiment to facilitate our analyses of the experimental results. Table 1 shows an example information structure. At the initiation of an experiment, traders do not know the quality of their information nor do they know what information others possess. They can only learn by observing their own information set, their transactions, and price changes.

Four groups of four subjects each were used in our experiments. Five different experiments were conducted with each group. With pay-for-performance we were able to get all subjects and groups to agree to complete and to actually complete the full set of five experiments. Each of the first two groups were comprised of four Ph.D. students with no common members. Group 3 consisted of four undergraduate students, two majoring in accounting and two in finance. Group 4 included two second-year MBA students concentrating in finance and two first-year MBA students who had not yet decided on any concentration. Each experiment consisted of 40 trading (decision) periods. Thus, each subject participated in 200 trading periods. As noted earlier, the first 20 periods in each

Table 1. An Example Information Structure for Traders in an Experiment

Traders	Information Structure
1	(X,II,X,I,II,I)
2	(I,X,II,X,I,II)
3	(II,X,I,X,II,I)
4	(X,I,X,II,I,II)

Table 2. Average and Cumulative Average Excess Returns (in %) from Periods 21 to 40 for Traders on Their Type X, I, and II Stocks

	Type X Stock		Type I Stock		Type II Stock	
Periods	AR	CAR	AR	CAR	AR	CAR
21	0.30	0.30	0.57	0.57	0.14	0.14
22	0.01	0.31	−0.23	0.34	−0.27	−0.13
23	−0.20	0.11	0.14	0.48	0.17	0.30
24	−0.31	−0.20	0.54	1.02	0.41	0.44
25	−0.14	−0.34	−0.27	0.75	−0.19	0.25
26	0.40	0.06	0.35	1.10	0.05	0.30
27	−0.09	−0.03	0.95	2.04	0.17	0.47
28	−0.01	−0.04	0.23	2.28	0.45	0.92
29	−0.08	−0.12	−0.05	2.22	−0.35	0.57
30	0.07	−0.05	0.17	2.40	−0.08	0.49
31	0.06	0.01	0.03	2.43	0.43	0.92
32	0.48	0.50	0.74	3.17	0.95	1.87
33	0.24	0.74	0.05	3.22	−0.23	1.64
34	0.32	1.06	0.11	3.33	0.36	2.00
35	0.24	1.30	0.07	3.40	0.19	2.19
36	0.24	1.54	0.43	3.83	0.09	2.28
37	−0.09	1.45	−0.09	3.74	−0.21	2.07
38	−0.01	1.44	0.85	4.59	0.47	2.53
39	−0.43	1.00	−0.41	4.18	−0.49	2.04
40	0.43	1.44	0.76	4.94	0.66	2.69

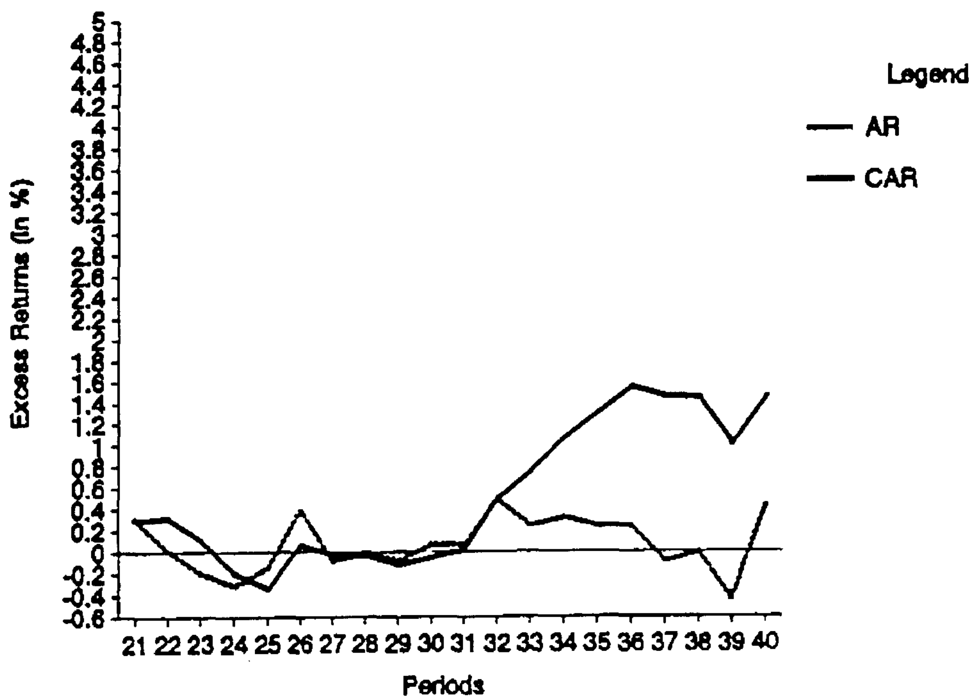

Figure 1. Average and cumulative average excess returns on type X stocks.

experiment were used as the historical periods for computing the necessary coefficients of the market model. The observations from the second 20 periods were used in performing the analyses that follow. We set subject performance-based rewards at levels common in recent induced value experimentation, that is, an average of approximately \$17.50. The payments ran from a low of \$5 (the prescribed "show-up" fee) to a high of \$30 for a session that lasted approximately an hour. Given a subject payment grant of \$1500, we were able to experiment with four groups, each completing the full set of five experiments (i.e., $4 \times 4 \times \$17.50 \times 5 = \$1400$ in expected payouts with a \$100 reserve to cover contingencies).

Data Results and Analyses

The intercept and coefficient of the market model (αs and βs) were calculated using data from the first 20 periods. Each trader's excess return computations use the last 20 periods (periods 21 to 40). As detailed in the first section, a carefully designed electronic market enables us to have the knowledge of each trader's information quality on each stock. When applied in conducting field studies, the market model uses the real return of each stock to calculate excess return for stocks due to the inability of identifying insider stocks. However, because of the ability to identify insider stocks in our experiments, we modify the market model to calculate traders' excess returns. That is, trader j's excess return on stock i during period t is calculated as follows:

$$AR_{jit} = TR_{jit} - (\alpha_i + \beta_i R_{mt})$$

where AR_{jit} is trader j's excess return on stock i during period t; TR_{jit} is trader j's true return on stock i during period t.

We also calculated the cumulative excess returns as:

$$CAR_{jit} = \Sigma AR_{jit}$$

Table 2 shows the average and cumulative average excess returns for experimental traders on their type X, I, and II stocks.

Figure 1 through Figure 3 show graphical comparisons of both average and cumulative average excess returns from period 21 to period 40 on traders' X, I, and II stocks.

From these figures we note that traders' average and cumulative average excess returns on type I stocks are greater than that on type II stocks and further greater than that on type X stocks. While the cumulative returns are positive (and thus all the CAR graphs tend in an upward direction), the cumulative returns for those relating to type I information and type II information (see Figures 2 and 3) are positive early on and increase more steeply than that relating to type X information. While Figure 1 indicates that public information enables traders to earn positive rewards, the rewards are not at the rate or level associated with the higher quality type I or type II information. We perform the following three formal hypothesis tests before stating our conclusion about these returns:

H_{1o}: $AR_X \leq 0$
H_{1a}: $AR_X > 0$

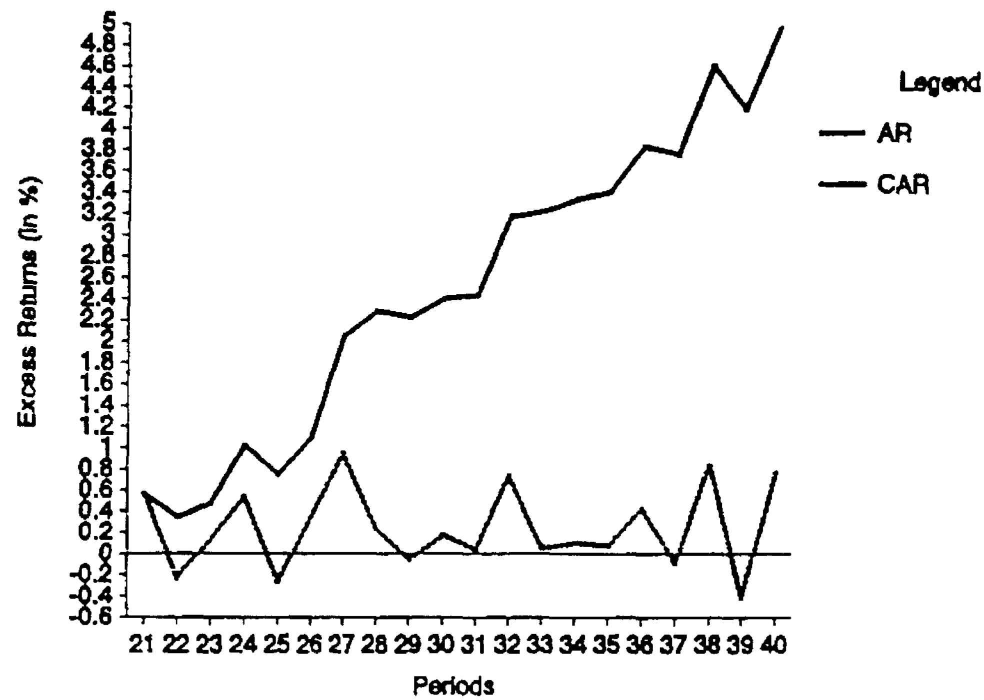

Figure 2. Average and cumulative average excess returns on type I stocks.

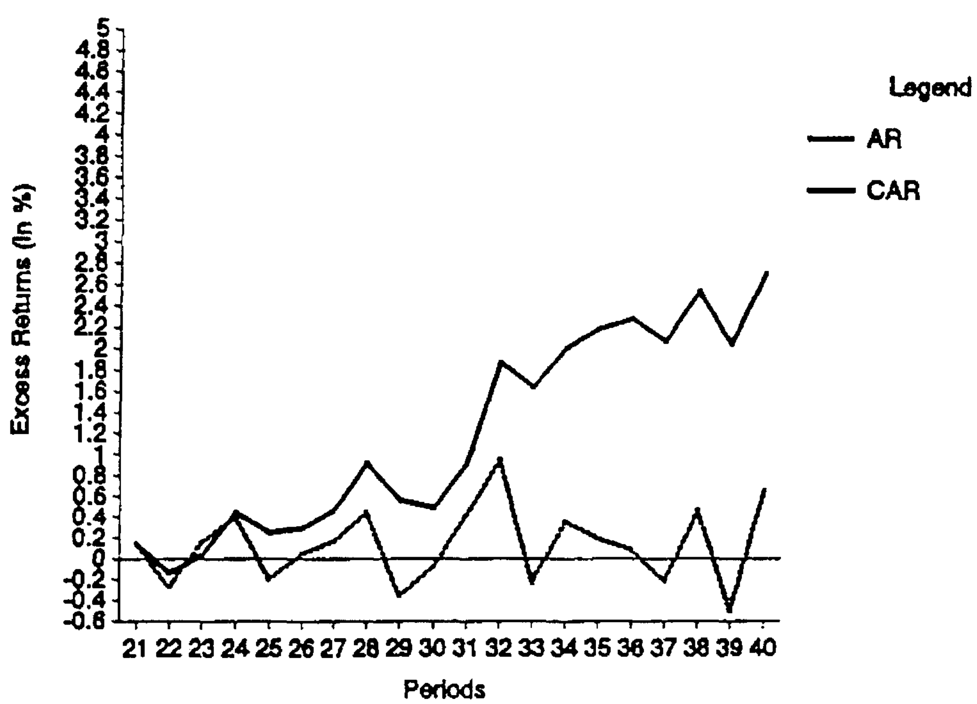

Figure 3. Average and cumulative average excess returns on type II stocks.

Table 3. Test Results of Hypotheses 1, 2 and 3

Hypotheses	Test Statistic (Z)	Result $\alpha = 0.1$	$\alpha = 0.05$	$\alpha = 0.01$
H1	0.97	F	F	F
H2	2.39	R	R	R
H3	1.31	R	F	F

one sided $Z_{0.1} = 1.28$; one sided $Z_{0.05} = 1.65$; one sided $Z_{0.01} = 2.3$.
R = reject the null hypothesis; F = fail to reject the null hypothesis.

H_{2o}: $AR_I \leq 0$
H_{2a}: $AR_I > 0$

H_{3o}: $AR_{II} \leq 0$
H_{3a}: $AR_{II} > 0$

All of our hypotheses are designed as one-sided tests. Since we had no basis to assume the normality or any other underlying distributional form of traders' returns on stocks, we used the non-parametric Wilcoxon signed rank test. The theoretical Z values for the three significance levels we used are: $Z_{0.1} = 1.282$, $Z_{0.05} = 1.645$, and $Z_{0.01} = 2.3$. We used R to indicate a rejection of the null hypothesis and F a failure to reject the null hypothesis. Table 3 provides the test results for H1, H2, and H3.

From the test results we conclude that statistically significantly (at all three significance levels) type I traders earned abnormal excess returns. For type II traders, only when the significance level is $\alpha = 0.1$ would we conclude that traders have statistically significant abnormal returns. The failure to reject null hypothesis H1 at all three significance levels indicating that traders who did not have inside information about stocks did not earn statistically significant excess profits.

Summary Comments

Our work provides an alternative way of investigating issues concerning market efficiencies rather than using the traditional field study approach. The laboratory environment provides a means to carefully control the variables of interest and accurately record and track both individual participant and market outcomes. Smith (1976) also posits that the results of laboratory experiments can serve as an empirical pre-test of economic theory prior to field tests and that laboratory investigations are relevant to the structuring and interpretation of field data. Due to the difficulties and constraints in analyzing information value in a real market, we proposed using laboratory experiments and designed a market shell for this purpose. The control we were able to exercise in the experiments was a key factor in our ability to complete the analyses.

But induced value laboratory experimentation is not without its limitations. As Smith has noted on several occasions, the applicability of the results rests upon the experiments paralleling the intended application environment in salient characteristics. As in any analysis, it is possible to miss key variables or fail to select important underlying relationships to be studied. Smith's (1976) foundation article carefully sets out the postulates and processes of induced laboratory experimentation.

We conclude our findings in this research as follows:

1. A positive relationship between information quality and trading profits in a market was identified;
2. results contradict the strong form EMH;
3. results support the semi-strong form EMH.

Global electronic markets can provide rapid and relatively cheap means to accomplish business transactions. If we are to design effective rules and procedures that facilitate the workings of such markets and attain equal footing for traders, we must deepen our understanding of relationships that we began to study in this research.

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