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THE SPEED OF ADJUSTMENT OF PRICES TO PRIVATE INFORMATION: EMPIRICAL TESTS

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Abstract

We estimate speeds of adjustment of individual stock prices to private information using daily data. We use a model in which private information gives rise to return variance and private information decays linearly over time. We find that, on average, about 85 percent to 88 percent of private information is incorporated into prices within one trading day, with variation depending upon the stock's trading volume and whether the stock is listed on an exchange. The findings support strong form market efficiency.

I. Introduction

In this paper we explore how quickly stock prices adjust to private information. Recent theoretical and empirical research points to the dominant influence of private information on price volatility. The models of Kyle (1985) and Foster and Viswanathan (1990) view private information as determining price volatility. French and Roll (1986), Barclay, Litzenberger, and Warner (1990), and Barclay and Warner (1993) all provide evidence that the trades of privately informed traders are the primary movers in stock prices, not the trades induced by public information. If there is a relation between the observable variance of market price and the unobservable variance induced by private information, price volatility should decay as prices come to reflect private information. Our tests use the decay of market price volatility to measure the speed with which private information is absorbed into prices.

Tests of strong form efficiency seldom examine the speed of adjustment of prices to private information. Fama (1991), for example, discusses which

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investors have access to private information and which obtain abnormal returns, but cites no studies of how quickly prices adjust to private information. Measuring the speed of adjustment of prices to private information directly tests the strong form efficiency of the stock market, just as measuring the speed with which prices reflect public announcements tests semi-strong form efficiency. If prices reflect private information rapidly, it is consistent with strong form efficiency.

Measuring directly how fast prices reflect private information is difficult. No database exists that identifies trades based upon private information. Nevertheless, several types of studies, generally emphasizing other concerns, provide evidence on this question. Insider trading studies (Rozeff and Zaman (1988)) report that abnormal returns tend to cumulate for months after insider trades. These studies suggest that market prices adjust slowly to private information and that the stock market is strong form inefficient. The studies measure abnormal returns over long intervals. However, the findings could be sensitive to the measurement of abnormal returns, given the evidence that insiders tend to buy low and sell high and that beta coefficients change as price changes. A case study of the Campbell Taggert merger provides a far different picture. In this instance, insider trading about the prospective merger led to a rapid spread of information and, within days, precipitated a public announcement (Cornell and Sirri (1992)). Similarly, Meulbroek's (1992) examination of illegal insider trading suggests that price responds rapidly to insider trading. In a different vein, Holthausen, Leftwich, and Mayers (1990) examine the speed at which stock prices respond to large block transactions and find that, where there are permanent price adjustments, they respond quickly. All of these findings support a rapid price adjustment to private information and strong form market efficiency.

We estimate speeds of adjustment to private information across large samples of stocks and find several cross-sectional regularities. For both exchange-listed and over-the-counter stocks, private information requires slightly more than one day to be absorbed into prices. This suggests that the major U.S. stock markets are largely strong form efficient. The evidence is consistent with French and Roll's (1986) observation that, to rationalize the observed pattern of daily return variance ratios, private information is absorbed over several days. For exchange-listed stocks, we estimate that 88.3 percent of the private information that informed traders have at the beginning of each trading day is absorbed in one day for the average stock. This speed of adjustment depends slightly on the average daily trading volume. For over-the-counter stocks, an average of 85.1 percent of private information is absorbed in one day. The adjustment rate rises monotonically from 80.6 percent for the lowest-volume stocks to 89.6 percent for the highest-volume stocks. Over-the-counter stocks have lower speeds of adjustment than exchange-listed stocks, holding trading volume constant. Stocks with greater trading volume have higher speeds of adjustment than stocks with lower trading volume, holding constant whether the stocks are exchange listed.

If private information traders prefer to trade when liquidity traders are active in the market (Admati and Pfleiderer (1988)), stocks with higher trading volume are likely to have faster speeds of adjustment. Traders in over-the-counter stocks can conceal information more easily since they are dealing with multiple market makers, causing slower speeds of adjustment. By contrast, exchange specialists have an incentive to average profits over time to detect privately held information and reduce adverse selection, causing faster dissemination of private information in prices of exchange-listed stocks.

The usual definition of strong form efficiency, as the condition where prices reflect all information at every instant, ignores trading costs and imperfect information, which sometimes induce privately informed traders not to trade. We define strong form efficiency as the condition where prices rapidly reflect private information that is traded upon. Strong form efficiency in this sense is expected because trading itself reveals private information. This provides an incentive for traders to trade quickly before the information loses its value. In addition, traders fear competitive sources of the information, or may expect a related public announcement in the near future. The trader also has an incentive to limit the holding period of risky securities. Any trader, except insiders operating under legal time restrictions, wants confirming public information to come to light shortly after the private information trades have been completed.

II. The Model

To obtain an empirically estimable equation that relates the speed of price adjustment to private information, we extend the models of Kyle (1985) and Foster and Viswanathan (1990). Their models assume an informed trader, a market maker, and uninformed liquidity traders who trade a single asset in a continuous auction market. At the start of each trading day d, the informed trader assesses an informed price, IP_d, based upon private information. We assume the informed prices evolve as:

$$IP_d = IP_{d-1} + e_d, \quad e_d \sim N(0, h_d) \tag{1}$$

$$h_d = a + u_d. \tag{2}$$

The informed prices follow a random process with mean zero increment. The variance of noise in the private price, h_d, reflects the effect of public information.

Since prices quickly reflect public information, we assume h_d has mean a and serially uncorrelated (random) shock u_d. The latter term eventually appears as the error term in our regression model. The market maker adjusts prices according to the order flow arriving from informed traders and liquidity traders.

Price overreaction as a source of variance is beyond the scope of this model. Existing evidence is conflicting. Some findings suggest that overreaction is not a major factor influencing stock prices. For example, French and Roll (1986) find that noise accounts for a small fraction of variance as compared with private information. Eckbo and Liu (1993) find that the size of temporary components in aggregate returns is small, especially in the period following World War II. However, Lakonishok, Shleifer, and Vishny (1994) provide new evidence that contrarian strategies produce abnormal returns. Given the lack of consensus concerning overreaction and the modeling difficulties, we do not investigate overreaction in this paper.

We denote the informed trader's asset holdings on day d by $x_{d,t}$, where t refers to the time during the trading day d. The value $t = 0$ refers to the open of trading and $t = 1$ refers to the close of trading. Changes in the informed trader's holdings represent the trading strategy and are denoted by $dx_{d,t}$. Correlated noise traders are absent from the model. Liquidity traders trade randomly at the market price. The market maker sets prices. The model shows that the sensitivity of prices to order flow is directly related to the informed trader's information and inversely related to the order flow of liquidity traders. If variation in private information through time is greater than variation in the rate at which liquidity traders submit orders, price volatility will depend primarily on the rate of information flow. Similarly, Ross (1989) assumes that prices depend on information, and he produces a model in which lack of arbitrage profits implies that variance of price equals variance of information flow.

Changes in the holdings of liquidity traders are denoted $dl_{d,t}$. These follow a stochastic process with zero mean and standard deviation s:

$$dl_{d,t} = s\,dz \tag{3}$$

where dz is a Wiener process. The parameter s is the order submission rate of liquidity traders.

The market maker observes the total quantity traded by both informed and uninformed traders. Following Kyle (1985), the market maker's price change, $dP_{d,t}$, is proportional to the total quantity transacted:

$$dP_{d,t} = \lambda_{d,t}(dx_{d,t} + dl_{d,t}), \tag{4}$$

where $\lambda_{d,t}$ measures the sensitivity of the price to the order flow. The informed trader's change in holdings is a function of the difference between the informed price and the price set by the market maker, times the sensitivity of the informed trader to the difference, denoted $\beta_{d,t}$. $P_{d,t}$ is the price set by the market maker.

$$dx_{d,t} = \beta_{d,t}(IP_d - P_{d,t})dt, \tag{5}$$

Substituting (3) and (5) into (4) gives the diffusion process for $P_{d,t}$:

$$dP_{d,t} = \lambda_{d,t}[\beta_{d,t}(IP_d - P_{d,t})]dt + \lambda_{d,t}s\,dz. \tag{6}$$

The instantaneous standard deviation of price changes is $\sigma_{d,t}(dP) = \lambda_{d,t}s$. The standard deviation of price changes is measurable, but $\lambda_{d,t}$ and s are not. However, Foster and Viswanathan (1990) provide a bridge between unobservable and observable variables.

Let $\sigma^2_{d,t}(IP)$ be the variance of the informed price IP_d around the price $P_{d,t}$ set by the market maker, i.e.,

$$\sigma^2_{d,t}(IP) = E[(IP_d - P_{d,t})^2]. \tag{7}$$

where $E[\bullet]$ is the expectation operator. At the market opening on day d, the variance is denoted by $\sigma^2_{d,0}(IP)$, which measures the information of the informed trader at the opening. The residual information held by the informed trader at the closing is measured by the closing variance $\sigma^2_{d,1}(IP)$. Foster and Viswanathan (1990, Theorem 1) show that optimizing behavior by the informed trader leads to:

$$\sigma_d(dP) = \lambda_{d,t}s = \lambda_d s = (\sigma^2_{d,0}(IP) - \sigma^2_{d,1}(IP))^{\frac{1}{2}}. \tag{8}$$

That is, given the opening and closing variances, the market maker's sensitivity of price to order flow, $\lambda_{d,t}$, is constant on day d. Therefore, assuming s remains constant, the standard deviation of price change on day d is a function of the difference between the variances (of informed price around market price) at the open and the close.

To derive an empirically testable equation, we assume that private information decays linearly during the day, that is,

$$\sigma^2_{d,1}(IP) = (1 - \alpha)\sigma^2_{d,0}(IP). \tag{9}$$

where $0 < \alpha \leq 1$. That is, a proportion of private information, $\alpha\sigma^2_{d,0}(IP)$, is assumed to be incorporated into prices via trading by the end of day d. The parameter α measures the speed of decay of information. If $\alpha = 1$, the variance at the close is zero, meaning that the closing price equals IP_d and there is no residual information. The condition that $\alpha > 0$ means that the informed trader does not throw away information but trades upon it, such that some information is revealed in prices. We do not, of course, expect (9) to hold exactly. However, linearity approximates various possible functional relations between time and privately held information.

Equation (9) leads to a testable model. First, from (1) and (9),

$$\begin{aligned}\sigma^2_{d,0}(IP) &= \sigma^2_{d-1,1}(IP) + h_d \\ &= (1-\alpha)\sigma_{d-1,0}(IP) + h_d.\end{aligned} \tag{10}$$

Since variances measure information, (10) says the information at the open is the sum of the residual information from the prior day's close plus new information. The parameter α is the speed of adjustment parameter. If $\alpha = 1$, all of the private information on the previous date is incorporated into prices and, as a result, the variance of the informed price on day d is the variance of the innovation in the informed trader's price. On the other hand, if α is small or close to zero, the residual private information has a relatively large weight in the variance of the informed price. Second, using (9) in (8) gives

$$\begin{aligned}\sigma^2_d(dP) &= [\sigma^2_{d,0}(IP) - \sigma^2_{d,1}(IP)] \\ &= [\sigma^2_{d,0}(IP) - (1-\alpha)\sigma^2_{d,0}(IP)] \\ &= \alpha\sigma^2_{d,0}(IP),\end{aligned} \tag{11}$$

which says that the observed daily price variance is proportional to the unobservable variance of informed price around market price.

Combining (10) and (11) produces a testable model:

$$\sigma^2_d(dP) = \alpha a + \alpha u_d + \sigma^2_{d-1}(dP) - \alpha\sigma^2_{d-1}(dP). \tag{12}$$

We write this as a regression such that α can be estimated:

$$\Delta\sigma_d^2(dP) = b - \alpha\sigma_{d-1}^2(dP) + \zeta_d, \tag{13}$$

where $\Delta\sigma_d^2 = \sigma_d - \sigma_{d-1}$, $b = \alpha a$, and $\zeta_d = \alpha u_d$.

We check the specification of (13) in several ways.[1] Recall that the effect of public information on variance is u_d, which is captured in the residual of (13). If the market is semi-strong form efficient and prices reflect public information quickly (see Fama (1991)), the residuals of (13) should be independent. We check the average first-order autocorrelation coefficients of the residuals of (13) and find them to be insignificant. Hence, the residuals of (13) appear to be independently distributed. The residuals of (13) might not be identically distributed if pronounced day-of-the-week effects occur when public or private information is incorporated into prices. Similarly, estimates of α will be influenced if the rate of private information incorporation depends on the day of the week. We examine the residuals and estimates of α for day-of-the-week effects and do not find any.

Estimates of $(1-\alpha)$ can be obtained from (12) by regressing daily variance on its lag, i.e., by obtaining the first-order autocorrelation of daily variances. If private information is absorbed in one trading session, estimates of α are one, and the first-order autocorrelations of daily variances are zero. The intuition is that each day's variance is distinct because private information is generated anew each day and is reflected in prices in just one day. If private information is carried over for many days, α is small and daily variances are highly autocorrelated. A large literature on variance nonstationarity suggests that the first-order autocorrelations of daily variances are not zero.[2] This leads us to expect that estimates of α do not equal one. Empirically, we find that estimates of α are significantly less than one.

III. Estimates of Speed of Adjustment

If prices incorporate a proportion α of private information on every trading day, then, according to (13), the change in volatility is inversely related to the level of volatility in the previous period. We estimate the parameter α by regressing the change in daily volatility on the prior day's volatility. To do this, we require estimates of daily volatility. Serial correlation in daily returns, induced by the bid-ask spread, is likely to affect measured estimates of daily volatility. Stocks with higher bid-ask spreads are likely to have greater noise in the estimates of daily volatility that can influence the estimates of α in (13). Hence, we must first purge the raw return data of bid-ask spread effects. Stephan and Whaley (1990, p. 203) provide theory and evidence that a moving average process

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[1]We thank an anonymous referee for suggesting these tests.

[2]For example, suppose daily variance has a mean m, that is, $\sigma_d^2(dP) = m + e_d$, where e_d is a mean zero error. This model is like (12) but has $\alpha = 1$. It is easy to show that this implies (13), with the restriction that $\alpha = 1$.

of order one, i.e., MA(1), succeeds in removing the bid-ask effect. We therefore estimate the variance of price changes on day d as the squared daily residual return of day d, where the residual return is obtained as the residual from estimating an MA(1) process (with a constant) for the observed daily returns:[3]

$$R^0_{i,d} = \mu_i + e_{i,d} - \theta e_{i,d-1}. \tag{14}$$

Here, $R^0_{i,d}$ is the observed daily return for stock i, μ_i is the constant, θ is the moving average paraneter, and $e_{i,d}$ is the disturbance. As Table 1 shows, this procedure removes bid-ask spread effects from daily returns since serial correlations at all lags are of no practical consequence after estimating the MA(1) model for each stock. We estimate (14) (and subsequently (13)) for two samples of stocks: (1) exchange-listed stocks, namely, 1,495 New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) stocks and (2) over-the-counter stocks, namely, 1,086 National Association of Securities Dealers Automated Quotation/National Market System (NASDAQ/NMS) stocks from January 2, 1988 to December 31, 1991. Center for Research in Security Prices (CRSP) files are the source of daily returns. The sample selection criteria are that the stock must have more than 300 daily returns over the four years and that the daily closing prices of the stock never fall below \$3 per share. When closing prices are absent but bid-ask spreads are present, we compute returns using the midpoint of the bid-ask spread. Days with missing returns and multiple-day returns are discarded; i.e., only adjacent daily returns are used.

Admati and Pfleiderer (1988) suggest that private information traders can trade more easily in markets with greater numbers of liquidity traders and greater trading volume. Hence, stocks with greater trading volume are likely to permit faster dissemination of private information into prices. For each sample, we rank each stock by its average daily trading volume, computed over the days the stock trades, and divide the samples into quintiles based upon average daily trading volume. We report results for full samples and for the trading volume quintiles. Presenting the average estimates of α within quintiles of trading volume helps gauge the importance of volume in the cross-sectional variation of parameter estimates and provides evidence that the estimates of α are economically meaningful and not simply statistical artifacts. For completeness, we also present estimates of θ by trading volume quintile. However, in this case also, theoretical arguments suggest that θ and volume are related. The moving average parameter θ of an MA(1) process is an inverse transformation of the first-order autocorrelation coefficient of returns. Since the latter is related to the bid-ask spread, θ should also be related to the bid-ask spread. Costs of transacting,

[3]Squared daily returns, or close variants, are used commonly as variance estimators.

TABLE 1. Estimates of the MA(1) Process to Remove the Bid-Ask Spread Effect.

$$R^0_{i,d} = \mu_i + e_{i,d} - \theta e_{i,d} \tag{14}$$

Mean Estimate	Full Sample	By Average Daily Trading Volume: Smallest	2	3	4	Largest
Panel A. NYSE and AMEX Stocks						
θ	-0.006	0.022	0.003	-0.001	-0.031	-0.024
	(0.003)	(0.008)	(0.007)	(0.007)	(0.006)	(0.004)
μ(%)	0.067	0.051	0.062	0.077	0.074	0.073
	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
No. of firms	1495	299	299	299	299	299
Residual Autocorrelation						
ρ_1	0.001	0.002	0.000	-0.000	0.002	0.003
ρ_2	-0.003	0.014	0.007	-0.006	-0.010	-0.024
ρ_3	-0.018	-0.004	-0.012	-0.018	-0.022	-0.033
Panel B. NASDAQ/NMS Stocks						
θ	0.249	0.533	0.390	0.249	0.102	-0.029
	(0.007)	(0.009)	(0.009)	(0.008)	(0.007)	(0.005)
μ(%)	0.097	0.087	0.091	0.092	0.102	0.113
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
No. of firms	1086	217	217	218	217	217
Residual Autocorrelation						
ρ_1	-0.006	-0.009	-0.010	-0.008	-0.003	0.000
ρ_2	0.006	-0.002	0.005	0.018	0.014	-0.005
ρ_3	0.003	0.008	0.018	0.017	-0.002	-0.027

Note: $R^0_{i,d}$ is the observed rate of return on stock i on date d, μ_i is the mean of the observed returns, and $e_{i,d}$ is a random innovation. As suggested by Stephan and Whaley (1990), the innovations from the MA(1) process should be serially uncorrelated and purged of the bid-ask effect. We estimate the MA(1) model for each of the 1495 NYSE and AMEX stocks and 1086 NASDAQ/NMS stocks using daily data from January 2, 1988 through December 31, 1991. The sample selection criteria are (1) that the stock must have more than 300 daily returns on the 1991 CRSP tapes over the four-year period and (2) that the daily closing prices of the stock never fall below $3 per share in the sample period.

including bid-ask spreads, tend to inhibit trading. Hence, we expect θ to be related to volume.

Table 1 reports descriptive statistics resulting from estimating daily residual returns for each stock according to (14). The first three residual autocorrelations of the MA(1) model average close to zero. In terms of removing bid-ask spread effects, this indicates that the model removes return autocorrelations. The average first-order moving average parameter is small and slightly negative for exchange-listed stocks, indicating a tendency for positive autocorrelation in the daily returns of these stocks. By contrast, the first-order moving average parameter of the NASDAQ/NMS stocks averages 0.249, indicating that daily returns are negatively autocorrelated. Presumably, the bid-ask bounce is more prevalent in the daily returns of NASDAQ/NMS stocks. The moving average parameter declines monotonically for these securities as trading volume quintile rises, suggesting that the bid-ask bounce is less influential in the daily returns of stocks with greater trading volume.

Using squared residuals from the estimated MA(1) process of each firm to estimate daily variance, we estimate (13) for each firm. Table 2 summarizes the findings averaged across volume quintiles. The mean estimate of α for the NYSE/AMEX sample is 0.883, and the range is 0.354 to 1.018. Given a standard error of the mean of 0.002, adjustment coefficients are significantly less than one, on average. The estimate suggests the presence of residual private information on the following day. The model predicts that tomorrow's beginning stock of private information is 0.117 of today's, and that in two days the stock of information is $(0.117)^2 = 0.014$ of today's. Hence, we find that the price adjustment to private information is virtually complete in two days. For the NYSE/AMEX sample, there is a visible but slight tendency of the speeds of adjustment to rise with trading volume.

The price adjustment to private information is slower for NASDAQ/NMS stocks, averaging 0.851. A t-test comparing the means of the two samples is 10.15, indicating a significant difference. The results are reported in Table 3. For the NASDAQ/NMS stocks, the mean α again is significantly less than one. The relation of volume to speed of adjustment to private information is clearer for these stocks. The average α rises from 0.806 to 0.896 monotonically with volume quintile. However, even a value of 0.806 indicates that all but a small fraction of private information is absorbed into prices within two trading days.

Table 3 shows t-tests comparing the price-adjustment coefficients by quintile of trading volume of exchange-listed and NASDAQ/NMS stocks. For the smallest three quintiles and for the sample averages, we find evidence of significant differences in estimated coefficients. Hence, even though these tests suggest rapid dissemination of private information into prices for listed and unlisted stocks, the quintile evidence shows a reliable difference in the speed

TABLE 2. Estimates of α, the Speed of Price Adjustment to Private Information.

$$\Delta\hat{\sigma}^2_{i,d} = b - \alpha\hat{\sigma}^2_{i,d-1} + \zeta_{i,d} \tag{13}$$

Mean Estimate	Full Sample	By Average Daily Trading Volume: Smallest	2	3	4	Largest
Panel A. NYSE and AMEX Stocks						
Summary of α Estimates						
Mean	0.883	0.876	0.877	0.889	0.885	0.890
Std. error mean	0.002	0.005	0.004	0.004	0.004	0.004
Median	0.897	0.896	0.890	0.902	0.897	0.900
Minimum	0.354	0.354	0.522	0.479	0.628	0.595
Maximum	1.018	1.009	1.013	1.010	1.011	1.018
Mean R^2	0.441	0.438	0.439	0.443	0.442	0.445
No. of firms	1495	299	299	299	299	299
Mean Residual Autocorrelation						
ρ_1	-0.005	-0.006	-0.007	-0.005	-0.005	-0.004
ρ_2	0.042	0.044	0.047	0.044	0.037	0.036
ρ_3	0.034	0.036	0.039	0.038	0.029	0.031
Average Daily Trading Volume (Shares)						
Mean	105,376	2,248	10,044	31,368	95,036	388,185
Median	29,773	2,209	9,581	29,773	92,773	304,266
Panel B. NASDAQ/NMS Stocks						
Summary of α Estimates						
Mean	0.851	0.806	0.818	0.851	0.883	0.896
Std. error mean	0.003	0.005	0.005	0.005	0.004	0.004
Median	0.859	0.812	0.820	0.862	0.895	0.911
Minimum	0.572	0.577	0.572	0.584	0.649	0.577
Maximum	1.001	0.955	0.991	0.986	0.998	1.001
Mean R^2	0.425	0.402	0.408	0.425	0.440	0.447
No. of firms	1086	217	217	218	217	217
Mean Residual Autocorrelation						
ρ_1	-0.009	-0.014	-0.013	-0.009	-0.006	-0.007
ρ_2	0.058	0.064	0.061	0.058	0.053	0.053
ρ_3	0.051	0.061	0.058	0.059	0.038	0.036
Average Daily Trading Volume (Shares)						
Mean	44,326	1,307	4,631	11,231	27,930	176,685
Median	10,823	1,264	4,321	10,823	26,839	99,601

Note: $\Delta\hat{\sigma}^2_{i,d} = \hat{\sigma}^2_{i,d} - \hat{\sigma}^2_{i,d-1}$ and $\hat{\sigma}^2_{i,d} = e^2_{i,d}$. $e_{i,d}$ is the rate of return, purged of bid-ask price effects, on stock i on date d, which is estimated from Table 1. Equation (13) is estimated for each of the sample stocks, which were selected from the NYSE, AMEX, and NASDAQ/NMS, and traded at a share price above $3 during the sample period. The estimate of α reflects the speed of price adjustment to private information. This table reports summary results for the whole sample and for the five subsamples based on the average daily trading volume.

TABLE 3. Comparisons of the Mean Speeds of Price Adjustment to Private Information Between Exchange-Listed and NASDAQ/NMS Stocks.

Mean Estimate	Full Sample	By Average Daily Trading Volume				
		Smallest	2	3	4	Largest
Exchange-listed stocks (α_1)	0.883	0.876	0.877	0.889	0.884	0.890
NASDAQ/NMS stocks (α_2)	0.851	0.806	0.817	0.850	0.883	0.896
t-stat. for H_0: $\alpha_1 = \alpha_2$	10.15	9.46	8.22	5.61	0.21	-0.98

Note: The mean speeds of price adjustment α are obtained in Table 2. The t-statistics test the null hypothesis that the means are equal in the two groups of stocks.

of absorption of private information, with NASDAQ/NMS stocks' showing slower absorption of private information.

To confirm these findings, we conduct tests on individual firm data. The tests explain the cross-sectional dispersion in estimated speeds of adjustment to private information by three variables. NMS_i is a dummy variable equal to one if the stock is NASDAQ/NMS and zero if the stock is NYSE/AMEX. VOL_i is the logarithm of the average daily trading volume. We use the log so that equal percentage increases in trading volume are given equivalent increases in weight. Similarly, $SIZE_i$ is the logarithm of average market value of equity of firm i over the sample period. This is computed as the average of the four year-end values. The regressions are conducted over a total of 2,581 stocks.

Model 2 in Table 4 contains NMS_i and VOL_i as independent variables. NMS_i is significantly negative and VOL_i is significantly positive. That is, stocks on NASDAQ/NMS tend to have lower price-adjustment coefficients and stocks with greater average trading volume tend to have higher price-adjustment coefficients. These findings are robust to the presence or absence of $SIZE_i$. The model in line three omits volume and introduces size. The dummy for listing remains significant. On the other hand, the model in line one introduces both volume and size. In this case, volume remains significant. With volume not present, size is significantly positive, indicating that larger firms have faster adjustment speeds. However, in the presence of volume, the size variable goes negative and is of borderline significance, despite its high simple correlation with volume. This suggests that volume is the meaningful variable in explaining speed of adjustment, not firm size.

NASDAQ/NMS and NYSE/AMEX stocks have different trading mechanisms. Although trading locale is associated with a statistically significant difference in the speed of adjustment to private information, the numerical size of the difference is small, only about 0.027. Traders can hide private information more easily in over-the-counter stocks because they are dealing with multiple

TABLE 4. Cross-sectional Analysis of α, the Speed of Price Adjustment to Private Information.

$$\alpha_i = a_0 + a_1 \text{NMS}_i + a_2\ \text{VOL}_i + a_3\ \text{SIZE}_i + e_i$$

Panel A. Estimated Coefficients (*t*-statistics in parentheses)

Model	a_0	a_1	a_2	a_3	R^2	F-value
1	0.8042	-0.0269	0.0114	-0.0029	0.08	75.95
	(62.07)	(-7.57)	(7.99)	(-1.79)		
2	0.7876	-0.0243	0.0093		0.08	112.21
	(86.69)	(-7.47)	(10.80)			
3	0.7885	-0.0217		0.0073	0.06	79.93
	(60.81)	(-6.14)		(7.39)		

Panel B. Correlations Among Variables

	α	NMS	VOL
NMS	-0.1981***		
VOL	0.2374***	-0.2374***	
SIZE	0.2144***	-0.4251***	0.7998***

Note: α_i is the estimate of the speed of price adjustment to private information for firm i, which is reported in Table 2; NMS_i is a dummy variable equal to one if stock i is listed on the NASDAQ/NMS and zero otherwise; VOL_i is the logarithm of the average daily trading volume; and SIZE_i is the logarithm of the average market value of equity for firm i over the sample period. These variables are obtained from the 1991 CRSP files. The regressions are conducted for the 1495 NYSE and AMEX stocks and 1086 NASDAQ/NMS stocks.
***Significant at the 1 percent level.

market makers. Also, specialists are theorized to give up profits to detect privately held information and reduce adverse selection. Although these suppositions are sensible and the data support them, the data do not suggest the effects are large.

Admati and Pfleiderer (1988) suggest traders with private information can hide their information more easily when liquidity traders are active in the market. If so, we expect faster adjustment speeds to private information when trading volume is greater. The data support this hypothesis. Again, however, the evidence does not suggest that a wide dispersion in absorption of private information arises when trading volumes differ among firms.

IV. Conclusion

Previous studies suggest that speculative markets absorb publicly available information rapidly. We examine how quickly prices reflect private information.

Since private information trading is not available, we rely on an extension of recent models (Kyle (1985), Foster and Viswanathan (1990)) that relate price variance to private information to derive an equation containing the speed of adjustment to private information.

We estimate the model for large samples of listed and over-the-counter stocks from 1988 to 1991 using daily data. The results indicate that, on average, about 85 percent to 88 percent of the private information the informed trader has at the beginning of each trading day is incorporated into prices by the end of the day. The stock of private information decays quickly; i.e., prices adjust to private information rapidly. Adjustment rates of prices to private information are slightly slower for over-the-counter stocks relative to exchange-listed stocks, and slightly faster for stocks with higher average daily trading volume.

Placing this evidence into context with the evidence of Cornell and Sirri (1992) and Meulbroek (1992) that market prices respond rapidly to insider trading, and with the evidence of Holthausen, Leftwich, and Mayers (1990) that prices respond rapidly to block trades, we conclude that market prices respond quickly to private information that is traded upon. Hence, the stock market is, by our definition, strong form efficient. Evidence to the contrary from insider trading studies (Rozeff and Zaman (1988)) could be due to nonstationary expected returns and should be reinvestigated.

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