Investment Analysis and the Adjustment of Stock Prices to Common Information

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In this article we are concerned with the effect of the number of investment analysts following a firm on the speed of adjustment of the firm's stock price to new information that has common effects across firms. It is found that returns on portfolios of firms that are followed by many analysts tend to lead those of firms that are followed by fewer analysts, even when the firms are of approximately the same size. Many analyst firms also tend to respond more rapidly to market returns than do few analyst firms, adjusting for firm size. This relation, however, is nonlinear, and the marginal effect of the number of analysts on the speed of price adjustment increases with the number of analysts.

In a recent paper Lo and MacKinlay (1990) report that current returns on a portfolio of small stocks are correlated with lagged returns on a portfolio of large stocks, but not vice versa. While such a finding could be the result of infrequent trading in small stocks, the authors demonstrate that unrealistically high non-trading frequencies would be required to account for their empirical results. This evidence, therefore, seems attributable to the fact that some stocks react faster

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than others to new information that has value implications across stocks, and which we therefore term *common information*.

This paper examines the relation between the speed of price adjustment to common information and the number of investment analysts following a firm. Recent theory suggests that the number of analysts may have an effect on the speed of adjustment to new information. For instance, Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993), in important extensions to the classic model of Kyle (1985), have shown that as the number of informed investors increases, the share price will reflect new information more rapidly; this would suggest an association between the number of analysts and the speed of adjustment, if the number of analysts can be regarded as a proxy for the number of informed investors.

In looking for the effects of the number of investment analysts on the speed of adjustment we hold firm size constant. We do this because we already know from the results of Lo and MacKinlay (1990) that size is related to the speed of adjustment; since there is a positive association between size and the number of analysts following a firm [Bhushan (1989)], finding that the number of analysts is positively associated with the speed of adjustment would not allow us to distinguish the number of analysts hypothesis from a pure size effect. Lo and MacKinlay offer no explanation for why size may be an important determinant of the speed of adjustment; one possibility is that size is positively associated with the number of individuals who are interested in a firm and therefore *know* about it [Merton (1987)], either because they already own the stock or because they gain information about the firm in the normal course of their business. A second possibility is that firm size proxies for trading volume and the latter may be related to the speed of price adjustment because of its effect on the informativeness of the stock price [see Admati and Pfleiderer (1988)]. By including the logarithm of firm size as well as the logarithm of share turnover in some of our tests we are able to determine whether there is an effect associated with size that is independent of trading volume and the number of analysts following the stock.

Broadly, our tests are of three kinds. First, we employ Granger causality regressions to determine whether, holding firm size constant, the returns on portfolios of *many analyst* firms (Granger) cause the returns on portfolios of *few analyst* firms and whether there is reverse causality.[1] We develop restrictions on the parameters of the Granger causality regressions that allow us to test the speed of adjustment hypothesis-that the many analyst firms react faster to common

[1] One variable is said to Granger-cause another if its lagged values are useful in predicting future values of the other. See Granger (1969) and Sims (1972).

information than do the few analyst firms. We find reliable support for this hypothesis.

The second test examines the pattern of price response of zero net investment, or "arbitrage," portfolios that are long in many analyst firms and short in few analyst firms of similar sizes to returns on the value-weighted index (VWI) and the equal-weighted index (EWI).[2] The returns on these market indices may be viewed as proxies for common information. We find that the returns on these arbitrage portfolios are negatively related to lagged returns on the EWI, which is consistent with slower price adjustment for the few analyst firms. Similar results are obtained for the two larger firm size quartiles when a VWI is used, but the results are more mixed for the smaller firm quartiles.

Finally, we examine whether the individual security betas with respect to the lagged returns on the VWI and the EWI are systematically related to firm size, share turnover, and number of analysts following the firm. Our results indicate that firm size, share turnover, and number of analysts are all highly significant in explaining lagged beta. The relation between the number of analysts and the speed of adjustment, however, appears to be nonlinear; a small number of analysts has little effect on the speed of adjustment.

The rest of the paper is organized as follows: Section 1 presents a simple model of lagged price adjustment and develops restrictions that form the basis for our tests. Section 2 presents the data, and Section 3 presents the Granger causality tests. Section 4 examines the timeliness of stock price reaction to the market, and Section 5 concludes.

1. A Simple Model of Lagged Price Adjustment

In order to lay the groundwork for our empirical analysis we consider in this section a simple model in which the returns on two portfolios respond to common information variables at different rates. Let $R_{M,t}$ and $R_{F,t}$ denote the returns on portfolios M and F on day t, where M and F refer to the portfolios of firms followed by *Many* and *Few* analysts respectively, and suppose that these returns can be written as lagged functions of the current and lagged values of K common factors, $z_{k,t}$, whose values are independently and identically distributed:

$$R_{M,t} = \alpha_M + \sum^{K} \beta_{M,k}(z_{k,t} + a_M z_{k,t-1}) + \epsilon_{M,t}, \tag{1}$$

[2] Both VWI and EWI are constructed with all firms in the New York and American Stock Exchanges and the NASDAQ.

$$R_{F,t} = \alpha_F + \sum_{k=1}^{K} \beta_{F,k}(z_{k,t} + a_F z_{k,t-1}) + \epsilon_{F,t}, \tag{2}$$

where $\epsilon_{M,t}$ and $\epsilon_{F,t}$ are the idiosyncratic shocks to the return processes $R_{M,t}$ and $R_{F,t}$. In the analysis in this section we assume that $\mathrm{Var}(\epsilon_{F,t}) = \mathrm{Var}(\epsilon_{M,T}) \equiv \sigma^2$.

In this model $\beta_{M,k}$ and $\beta_{F,k}$ determine the response of the portfolio returns to the contemporaneous common factors; a_M and a_F are lag response ratios, which provide a measure of the timeliness of stock price reactions. The lag response ratios are assumed to be the same for all factors. Without loss of generality, we assume that $\sigma^2_{z_k} = 1$ and, in keeping with our hypothesis that portfolio M responds more rapidly to new information, that $a_F > a_M$. Then the difference between the cross-serial covariances of $R_{F,t}$ and $R_{M,t-1}$, and of $R_{M,t}$ and $R_{F,t-1}$ is $(a_F - a_M)(\sum_{k=1}^{K} \beta_{F,k}\beta_{M,k})$, which is positive whenever the factor sensitivities of the two portfolios are of the same sign for each factor. In other words, the covariance between the current return on the more rapidly responding portfolio M and the lagged return on the less rapidly responding portfolio F is always less than the covariance between the current return on F and lagged return on M provided that the factor sensitivities are of the same sign. Under this assumption, the relative speeds of response can be assessed by examining the cross-serial covariances. In contrast, the autocovariances of the returns of portfolios M and F, $a_M \sum_{k=1}^{K} \beta^2_{M,k}$ and $a_F \sum_{k=1}^{K} \beta^2_{F,k}$, are not restricted by the assumption that portfolio M responds more quickly than portfolio F to new information. For example, if the return of portfolio F responds only to the lagged common factors,[3] then its serial covariance will be zero while the serial covariance of M will be positive for $a_M > 0$. On the other hand, if $a_M = 0$ and $a_F > 0$, then portfolio F will have a larger serial covariance than M. Therefore, we follow Lo and MacKinlay (1990) and focus on cross-serial covariances or correlations in our speed of adjustment tests rather than on autocovariances.

In order to derive a simple test for differences in the speed of adjustment, we perform Granger causality regressions that allow us to determine whether the returns on portfolio M are more useful in predicting the returns on portfolio F than vice versa. To understand the relation of the speed of adjustment to the Granger causality regressions, consider the following simplified version of the Granger causality regressions, in which each portfolio's return is regressed on its lagged value and the lagged value of the other portfolio return:

[3] In other words, $z_{k,t}$ does not appear in Equation (2)

$$R_{M,t} = b_0 + b_F R_{F,t-1} + b_M R_{M,t-1} + u_{M,t}, \tag{3}$$

$$R_{F,t} = g_0 + g_F R_{F,t-1} + g_M R_{M,t-1} + u_{F,t}. \tag{4}$$

The relation between the coefficients of the Granger causality regressions (3) and (4) and the speed of adjustment coefficients and factor sensitivities of Equations (1) and (2) are described in the following proposition, which is proved in the Appendix.

Proposition 1. *If the lag response ratio of portfolio F exceeds that of portfolio M (i.e., if $a_F > a_M$), then*

(a) $g_M > h_F$.

(b) If, in addition, the total factor sensitivities of M and F are equal–that is, $\beta_{M,k}(1 + a_M) = \beta_{F,k}(1 + a_F)\ \forall k$, then $b_M > b_F$ and $g_M > g_F$.

It should be noted that the cross-equation restriction in part (a) of the proposition obtains whenever the speed of adjustments differ in the hypothesized manner. The own equation restrictions in part (b) of the proposition, however, require somewhat stronger assumptions. Intuitively, the assumption in part (b) requires that the portfolios *M* and *F* be alike in all respects except the lag response ratio.

As discussed earlier, we control for the effect of size-related differences in the speed of adjustment by implementing the Granger causality tests with portfolios comprising firms of similar sizes. In order to control for the effect of other exogenous variables in our further tests of the speed of adjustment hypothesis, we employ a single measure of the speed of adjustment. To understand the nature of this measure, consider the Dimson-type regressions

$$R_{j,t} = a + b_{j,0} I_t + b_{j,1} I_{t-1} + u_t, \tag{5}$$

where $I_t \equiv \sum_{k=1}^{K} w_k z_{k,t}$ is a linear combination of the common factors.

The coefficients of regression (5) are related to the factor sensitivities and lag response coefficients in expressions (1) and (2) by

$$b_{j,0} = \frac{1}{\sigma_I^2} \sum_{k=1}^{K} w_k \beta_{j,k},$$

$$b_{j,1} = a_j b_{j,0}, \qquad j = M, F.$$

Although $b_{j,1}$ seems to be an obvious measure of lagged response to common information since it measures the lagged response to index *I*, it depends on $b_{j,0}$ as well as the lag response ratio a_j. Therefore, $b_{M,1} > b_{F,1}$ need not imply $a_M > a_M$ However, if $b_{M,0} > b_{F,0}$, then $b_{M,1} < b_{F,1}$ does imply that $a_M < a_F$. For later reference we state this as

Result 1. *A necessary condition for* $b_{M,1} < b_{F,1}$ *when* $b_{M,0} > b_{F,0}$ *is that* $a_M < a_F$.

It follows from this result that when $R_{M,t} - R_{F,t}$ is regressed on current and lagged values of *I*, a positive coefficient on *I*, and a negative coefficient on I_{t-1} will imply that the speed of response of portfolio *F* is less than that of portfolio *M*.

In the empirical analysis we report below, we run the Granger causality tests and Dimson regressions with multiple lags to allow for a more general setting in which information lags may exceed one period. We present tests of the restrictions corresponding to those developed in this section on the sum of the lagged response coefficients in these regressions.

2. Data

Daily stock returns and trading volume data for all firms were obtained from the CRSP NYAM-NASDAQ tapes from January 1977 to December 1988. The number of investment analysts following each firm was taken from the I/B/E/S tapes.[4] Our sample contains stocks in the I/B/E/S universe that were also in the CRSP database for five years[5] The number of analysts following a particular firm in a given year was defined as the number of analysts making an annual earnings forecast in December of the previous year.[6]

At the beginning of each year, firms were initially assigned to quartiles based on their market values of equity on the preceding December 31. Within each size quartile the firms were further divided into four size-ranked subgroups. Within each of these groups, four subgroups were formed based on the number of analysts following the firms, yielding 16 subgroups based on size and number of analysts ranks within each size quartile. Four portfolios were then formed from the 16 subgroups within each size quartile as follows: The subgroups with the fewest number of analysts in each of the four size classifications were combined to form the *Few* analysts portfolio. The *Many* analysts portfolio was formed by combining the subgroups having the most analysts within each size classification. Two intermediate analysts portfolios were formed in a similar fashion, yielding a total of four analyst-ranked portfolios within each size quartile. This procedure, designed to minimize the association between size and

[4] We are grateful to Lynch, Jones, and Ryan for giving us access to the I/B/E/S tapes.

[5] We use the same sample as Brennan and Hughes (1991).

[6] If a firm was included in the I/B/E/S database but was not followed by any analyst in a given year, then the number of analysts was taken as zero. We also repeated our tests excluding the zero. analysts groups and found results similar to those reported here.

Table 1
Statistics of size-analyst portfolio returns

Port-folio size, analyst	n	Mean, %	Std. dev., %	VR_3	VR_5	VR_{10}	VR_{20}
1, 1	112.7	0.1262	0.8587	1.571	1.567	2.044	2.654
1, 2	115.9	0.0996	0.8459	1.539	1.599	2.109	2.670
1, 3	114.9	0.0925	0.8617	1.565	1.599	2.047	2.569
1, 4	116.1	0.0933	0.9041	1.617	1.678	2.060	2.480
2, 1	119.4	0.0840	0.8572	1.513	1.524	1.824	2.117
2, 2	116.8	0.0817	0.8487	1.589	1.624	1.915	2.411
2, 3	117.1	0.0814	0.9219	1.617	1.633	1.994	2.413
2, 4	122.4	0.0792	0.9796	1.593	1.644	1.950	2.256
3, 1	120.0	0.0685	0.8451	1.549	1.560	1.850	2.109
3, 2	118.3	0.0776	0.8204	1.570	1.633	1.883	2.054
3, 3	119.9	0.0751	0.8885	1.603	1.666	1.952	2.142
3, 4	122.8	0.0670	0.9683	1.519	1.562	1.847	2.107
4, 1	121.5	0.0665	0.9469	1.342	1.402	1.575	1.579
4, 2	118.5	0.0675	0.9325	1.336	1.425	1.558	1.527
4, 3	121.2	0.0594	0.9391	1.307	1.376	1.472	1.418
4, 4	125.7	0.0606	0.9729	1.235	1.294	1.392	1.325

Statistics of daily returns of size-analyst portfolios over 1977-1988. *Size 1* refers to the smallest size portfolio. and Size 4 refers to the largest size portfolio. Similarly *Analyst 1* refers to the fewest number of analysts. and *Analyst 4* refers to the greatest number of analysts. The number of daily returns for all portfolios from 1977 to 1988 is 3033. *n* refers to the average number of firms in each portfolioover 1977-1988. VR_k refers to the k-day variance ratio, where $VR_k=[\mathrm{var}(R_{t,t-k})/k\mathrm{var}(R_{t,t-1})]$; and $R_{t,t-k}$ and $R_{t,t-1}$ are continuously compounded k-day and 1-day returns.

number of analysts within each size quartile, yielded 16 portfolios ranked first on size and then on number of analysts.[7] There were on average about 118 firms in each portfolio.

Table 1 reports the portfolio characteristics. There is some tendency within each size group for the mean return to decrease as the number of analysts increases, and the portfolio of small firms with the fewest analysts has by far the highest mean return.[8] Table 2 reports the median and average size of the firms in each portfolio and the median and average number of analysts following each firm in the portfolio. The median sizes of the firms in the different number of analyst portfolios within each size quartile are virtually the same. This indicates that we have been quite successful in reducing the association between size and number of analysts.

[7] We also considered forming a four-analysts group within each size quartile without the intraquartile size sorting. This simpler procedure, however, did not adequately control for size across the different analysts portfolios within a given size quartile.

[8] This is consistent with the findings of Arbel, Carrell, and Strebel (1983). However, Fama-Macbeth (1973) style regressions in which the mean returns on the 16 portfolios were regressed on estimated betas and number of analysts yielded no significance for the number of analysts.

Table 2
Statistics of size-analyst portfolio size and number of analysts

Portfolio	Size		Analysts	
Size, analyst	Median	Mean	Median	Mean
1, 1	0.0204	0.0197	0.4167	0.3546
1, 2	0.0214	0.0219	0.5833	0.6916
1, 3	0.0216	0.0228	1.2500	1.1769
1, 4	0.0215	0.0229	2.3750	2.6483
2, 1	0.0680	0.0702	0.5833	0.6795
2, 2	0.0695	0.0726	1.4167	1.6329
2, 3	0.0688	0.0731	2.7500	2.8810
2, 4	0.0690	0.0733	5.4167	5.8784
3, 1	0.2045	0.2178	1.5000	1.7615
3, 2	0.2050	0.2217	4.0833	4.0856
3, 3	0.2056	0.2250	6.2083	6.4435
3, 4	0.2056	0.2268	10.5833	10.9666
4, 1	0.9880	1.4325	6.6667	7.3437
4, 2	1.0021	1.6723	11.3750	12.3066
4, 3	0.9960	1.8012	15.4167	16.0158
4, 4	1.0073	2.5415	21.0833	21.6350

Statistics of size (in billions of dollars) and number of analysts making yearly forecasts in December for size-analyst portfolios obtained over 1977-1988. *Size 1* refers to the smallest size portfolio, and *Size 4* refers to the largest size portfolio. Similarly *Analyst 1* refers to the fewest number of analysts, and Analyst 4 refers to the greatest number of analysts. Statistics of portfolio size and number of analysts are obtained as follows: first the cross-sectional statistics (median and mean) of size and number of analysts are computed for each portfolio, each year; then the yearly cross-sectional statistics of each portfolio are averaged over time and reported above.

3. Granger Causality Tests

Table 1 reports the variance ratios for our 16 portfolios. If slow adjustment to new information manifests itself in positive autocorrelation, then we should expect to find that the few analyst, more slowly adjusting, portfolios have higher variance ratios. All of the variance ratios exceed unity which is consistent with the findings of Lo and MacKinlay (1988) and others of positive autocorrelation in portfolio returns at short horizons. There is a strong tendency for the small firm portfolios to have higher variance ratios than the large firm portfolios; however, only within the large size group is there much evidence that the portfolios with fewer analysts have higher variance ratios than those with more analysts. However, as we argued in Section 1, autocovariances, and therefore serial correlations, are unlikely to yield reliable inferences about the relative speeds of adjustment. Therefore, we turn to tests based on cross-serial correlations.[9]

[9] For comparison with Lo and MacKinlay (1990) we also computed cross-correlation matrices for lags up to five days (these results are not reported here in order to conserve space but are available from the authors on request). We found that, within size quartiles, returns on portfolios with fewer analysts had greater correlation with lagged returns of portfolio with many analysts than for the reverse case. As explained in Section 1. this is consistent with the many analyst firms adjusting to new common information more rapidly.

Table 3
Granger causality regressions for the size-analyst portfolio returns

Size (1)	LHS (2)	Few (3)	Many (4)	R^2 (5)	F_1 (6)	F_2 (7)
			A: 5 Lag regressions			
1	Few	0.1042	0.3517*	0.12	3.80†	1.99
	Many	0.2170*	0.2377*	0.10	0.02	
2	Few	0.0650	0.2635*	0.08	1.61	4.55†
	Many	0.0027	0.3872*	0.09	4.68†	
3	Few	0.0482	0.3139*	0.09	3.53‡	20.43*
	Many	−0.1914†	0.5123*	0.08	18.51*	
4	Few	0.1483	0.1034	0.05	0.05	1.34
	Many	−0.0704	0.2420†	0.03	2.15	
			B: 10 Lag regressions			
1	Few	0.0978	0.4215*	0.12	2.98‡	2.34
	Many	0.2080	0.2645*	0.10	0.08	
2	Few	0.0394	0.3153*	0.08	1.54	4.82†
	Many	−0.0638	0.4389*	0.09	3.98†	
3	Few	0.0487	0.3204*	0.10	2.03	14.70*
	Many	−0.2568†	0.5503*	0.08	13.36*	
4	Few	0.1790	0.0554	0.04	0.19	0.26
	Many	−0.0499	0.1894	0.02	0.66	

In column (2), Few (Many) indicates that the LHS variable is the return on the fewest (greatest) analysts portfolio within each size quartile. In columns (3) and (4), Few and Many refer to the sum of the slope coefficients of the lagged fewest analysts portfolio returns and most analysts portfolio returns respectively. F_1 is the F-statistic corresponding to the null that the sum of regression coefficients of "Few" is equal to that of "Many." F_2 is the F-statistic corresponding to the cross equation restriction $\Sigma_{k=1}^{K} b_{F,k} = \Sigma_{k=1}^{K} g_{M,k}$. This restriction implies that the impact of "Few" on "Many" (as measured by the sum of lagged regression coefficients) is equal to that of "Many" on "Few." R^2 refers to the adjusted coefficient of determination. l means significant at 1 percent level; † means significant at 5 percent level; ‡ means significant at 10 percent level.

In order to proceed more formally, and to reduce the number of statistical tests, we restricted our attention to the two portfolios within each size quartile that had the smallest and the largest number of analysts. These portfolios are referred to as *Few (F)* and *Many (M)* respectively. For each of the four pairs of portfolios, the following Granger causality regressions, which are generalizations of regressions (3) and (4), were run using daily returns:[10]

$$R_{M,t} = a_M + \sum_{k=1}^{K} b_{F,k} R_{F,t-k} + \sum_{k=1}^{K} b_{M,k} R_{M,t-k} + u_{M,t}, \qquad (6)$$

$$R_{F,t} = a_F + \sum_{k=1}^{K} g_{F,k} R_{F,t-k} + \sum_{k=1}^{K} g_{M,k} R_{M,t-k} + u_{F,t}. \qquad (7)$$

These regressions were fitted with 5 and 10 lags-with K = 5 and K

[10] If some stocks did not trade on a given day, then those stocks were dropped on that day and the portfolio return was computed as the average return of the other stocks in the portfolio.

= 10. If portfolio M adjusts to new information faster than portfolio F, then we expect from Proposition 1 a that the sums of the coefficients on lagged values of R_M in (7) will exceed the sum of the coefficients on lagged values of R_F in (6).

Table 3 presents the sums of the coefficients on the lagged values of R_M and R_F. Consider the estimates of the five-lag regression first. For the first three size quartiles the values of R_M reliably predict the returns on both portfolios M and F, while the sums of the coefficients on lagged values of R_F are typically not different from zero. For the largest size quartile there is no evidence that either set of lagged returns helps in predicting returns on portfolio F; however, the returns on the portfolio M are predicted by their own lagged returns but not by the lagged returns on portfolio F.

The sums of the coefficients are consistent with the restriction corresponding to Proposition la; that is, $\Sigma_{k=1}^{5} b_{F,k} < \Sigma_{k=1}^{5} g_{M,k}$ for each of the four pairs of regressions. The F-statistic (F_2 in Table 3) indicates rejection of the hypothesis that $\Sigma_{k=1}^{5} b_{F,k} = \Sigma_{k=1}^{5} g_{M,k}$ at the 5 percent and 1 percent levels for size quartiles 2 and 3 respectively. The F-statistic under the hypothesis that this restriction holds jointly for all the four size quartiles is 7.08, which indicates rejection at the 1 percent level. Turning to the restriction implied by Proposition lb, we find that the sum of the coefficients on the lagged values of R_M exceeds the sum of the coefficients on the lagged values of R_F in seven out of eight regressions and the differences in the sums are statistically significant in four regressions. The F-statistic under the hypothesis that sums of these coefficients in the eight regressions are jointly equal–$\Sigma_{k=1}^{5} b_{F,k} = \Sigma_{k=1}^{5} b_{M,k}$ and $\Sigma_{k=1}^{5} g_{F,k} = \Sigma_{k=1}^{5} g_{M,k}$–is 4.29, which is significant at the 1 percent level.

Finally, we note that in three out of four cases the returns on portfolio F are more predictable than the returns on portfolio M, as measured by the R^2; this is as we should expect if the prices of firms with few analysts react more slowly to new common information than those of firms with many analysts.

The results of the 10-lag regressions are similar to that for the 5-lag regressions. Moreover, the sums of the coefficients for the 10-lag regressions are close to the corresponding sums for the 5-lag regressions, indicating that there is little stock price reaction to information at lags longer than five days.

So far we have found that the lagged returns on portfolio M are more important than those of portfolio F in predicting returns on both portfolios, which is consistent with portfolio F adjusting more slowly to new information. In the following section we consider the role of the number of analysts in determining the speed of adjustment to new information contained in an index of market returns.

4. Timeliness of Reaction to Stock Market Returns

We first examine the speed of adjustment of portfolio values to market returns for the various size-analysts portfolios using the following regression:

$$R_{j,t} = a + \sum_{k=-K}^{K} b_{j,k} R_{m,t-k} + u_{j,t}, \tag{8}$$

where $R_{m,t}$ is the market portfolio return on day t. An estimate of the total sensitivity of portfolio j's return to the market is given by the sum of the slope coefficients, $\Sigma_{k=-K}^{K} b_{j,k}$.

The market return may be viewed as a linear combination of the contemporaneous common factors $z_{k,t}$. Define $LAG_j \equiv \Sigma_{k=1}^{K} b_{j,k}$, the sum of the coefficients on lagged market returns, and $LEAD_j \equiv \Sigma_{k=-K}^{-1} b_{j,k}$. LAG_j is a measure of the lagged price adjustment to common information. Similarly, LEAD, is a measure of the degree to which the returns on portfolio j anticipate or lead the returns on the market portfolio.

In order to determine the effect of the number of analysts on the rate at which security prices adjust to marketwide information, we estimated Equation (8) for each of the 16 size-analyst portfolios, using the VWI and the EWI. Figures 1*a* and 1*b* plot the cumulative fraction of the stock price reaction to market information realized by day *d* $(\Sigma_{k=-10}^{d} b_k/\Sigma_{k=-10}^{10} b_k)$for each portfolio using VWI as the market proxy. For instance, the value at $d = 0$ denotes the fraction of the information in the index returns incorporated in the prices on the date that the index returns are observed. For VWI returns, the graph is flat for $d < 0$ in all size quartiles, reflecting the fact that portfolio returns do not predict VWI returns. The large increase in the plots for $d = 0$ corresponds to the contemporaneous response coefficient. Most significant for our purposes is the increase in the level of the plots for $d = 1$, which corresponds to LAG,. As one would expect, LAG, is heavily influenced by firm size. Figures 2*a* and 2*b* plot the normalized cumulative slope coefficients using EWI as the market proxy. The results are qualitatively similar, although the large firms seem to forecast the EWI returns. Indeed, for the largest size quartile the sum of the slope coefficients on lagged EWI returns is negative for all analyst groups. To see that this result is to be expected when large firms adjust to new information more rapidly than the equal-weighted index, suppose that the returns on the EWI, $R_{E,t}$, and the returns on a large firm portfolio L, $R_{L,t}$, are functions of the current and laggedvalues of market index, 1,:

$$R_{L,t} = a_1 I_t + a_2 I_{t-1} + \epsilon_{L,t}, \tag{9}$$

$$R_{E,t} = b_1 I_t + b_2 I_{t-1}. \tag{10}$$

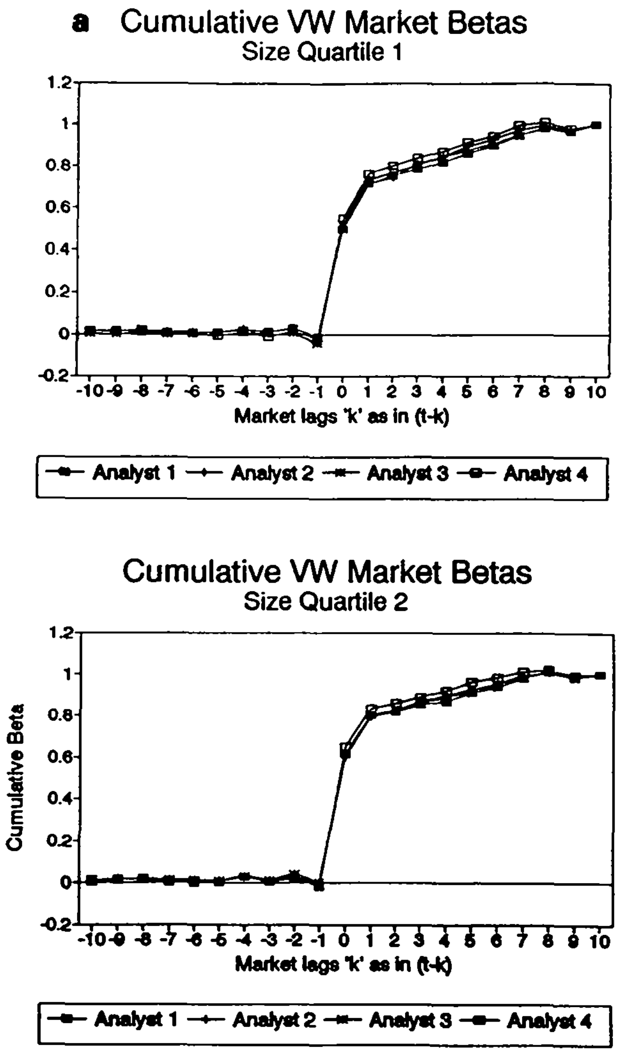


Figure 1
Normalized Cumulative Sums of the elements of the Dimson Beta Estimator using Value Weighted (VW) Market Index
The figures plot $\sum_{k=-10}^{d} b_{j,k}/\sum_{k=-10}^{10} b_{j,k}$ for $d = -10, \ldots, 10$ where $b_{j,k}$ are the coefficients from the regression $R_{j,t} = a + \sum_{k=-10}^{10} b_{j,k} R_{m,t-k} + u_{j,t}$.

Then it is easy to show that in a regression of $R_{L,t}$ on current and lagged values of $R_{E,t}$, the coefficient on $R_{E,t-1}$ is $[(b_1 a_2(b_1^2 + b_2^2) - b_1 b_2(a_1 b_1 + a_2 b_2)]/[(b_1^2 + b_2^2)^2 - b_1^2 b_2^2]$, which will be negative when $b_1/b_2 < a_1/a_2$–that is, when portfolio L responds more rapidly than portfolio E. Moreover, the coefficient decreases as the ratio a_1/a_2 increases–that is, the more timely are the returns on portfolio L.

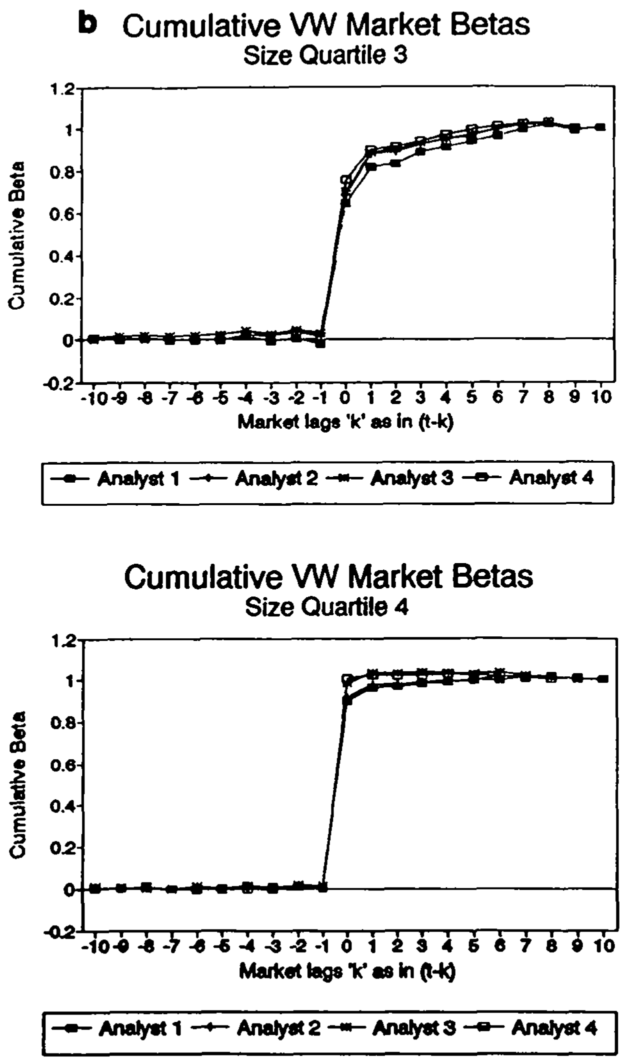


Figure 1 *Continued*

A formal test for the difference between the speed of response to common information of portfolios *M* and *F* was constructed as follows. For each size quartile the return on a zero net investment *arbitrage* portfolio denoted by *O*, which is long in portfolio *M* and short in portfolio *F*, was regressed against leads and lags of the return on the market portfolio:

$$R_{O,t} = a_O + \sum_{k=-K}^{K} b_{O,k} R_{m,t-k} + u_{O,t}. \tag{11}$$

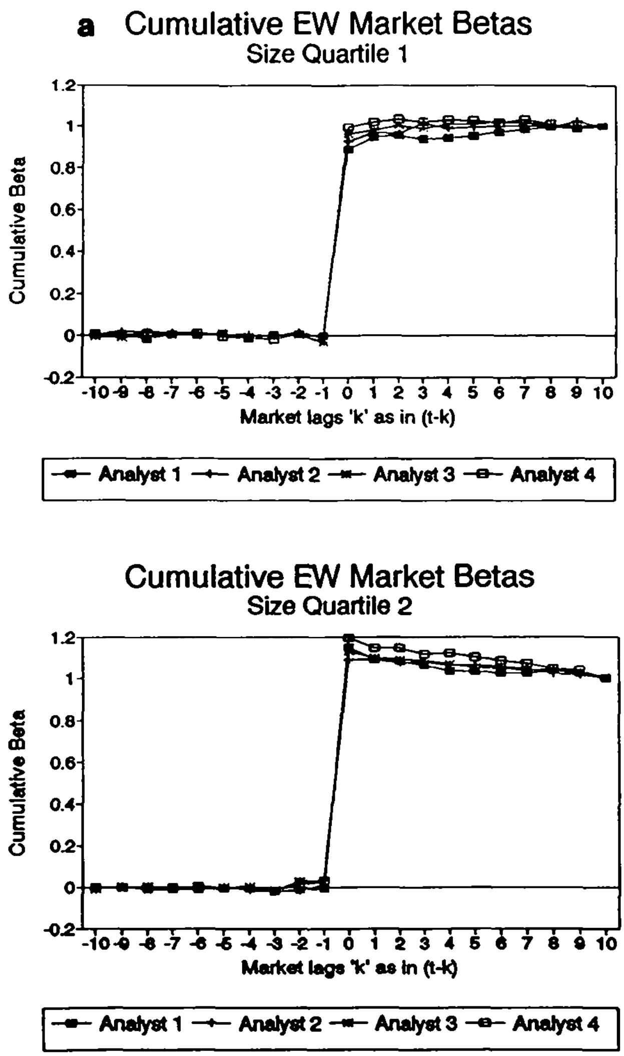
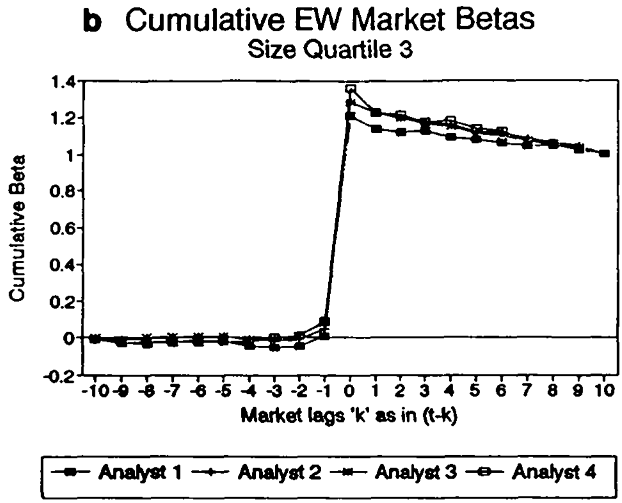


Figure 2
Normalized Cumulative Sums of the Dimson Beta Estimator using Equal-Weighted (EW) Market Index
The figures plot $\Sigma_{k=-10}^{d} b_{j,k}/\Sigma_{k=-10}^{10} b_{j,k}$ for $d=, -10, 10$ where $b_{j,k}$ are the coefficients from the regression $R_{j,t} = a + \Sigma_{k=-10}^{10} b_{j,k} R_{m,t-k} + u_{j,t}$.

Since $b_{O,k} = b_{M,k} - b_{F,k}$, the lag coefficients in regression (11) provide evidence on the relative speed of adjustment. Table 4 reports the results of these regressions for the four size quartiles using the VWI as the market proxy.

There is little evidence that current returns on the arbitrage port-



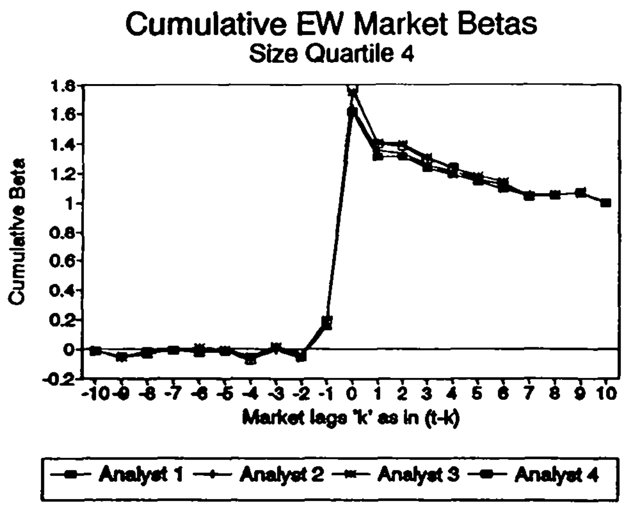


Figure 2 Continued

folios are associated with future returns on the value-weighted market portfolio. The value of $b_{o,0}$ is significantly positive for all size quartiles, indicating that M is more sensitive than F o contemporaneous market returns. Then Result 1 implies that if the sum of the coefficients on lagged returns is less than zero $(\Sigma_{k=1}^{K} b_{O,k} < 0)$, then the speed of adjustment of portfolio F is less than that of portfolio M. However, a positive sum of lagged return coefficients does not necessarily imply that the reverse is true, since $b_{o,0} > 0$ (see Result 1).

Table 4
Regressions of arbitrage portfolio on value-weighted index

Size	LHS	$\Sigma_{k=1}^{K} b_{o,k}$	$b_{o,0}$	$\Sigma_{k=-1}^{-K} b_{o,k}$	R^2
		A: 5 Leads/lags			
1	$R_{1,4,t} - R_{1,1,t}$	0.0094	0.0921*	−0.0089	0.02
2	$R_{2,4,t} - R_{2,1,t}$	0.0681*	0.1413*	−0.0112	0.11
3	$R_{3,4,t} - R_{3,1,t}$	−0.0524*	0.1649*	0.0323‡	0.12
4	$R_{4,4,t} - R_{4,1,t}$	−0.1014*	0.0460*	0.0054	0.04
		B: 10 Leads/lags			
1	$R_{1,4,t} - R_{1,1,t}$	−0.0482	0.0921*	−0.0117	0.03
2	$R_{2,4,t} - R_{2,1,t}$	0.0181	0.1413*	0.0071	0.11
3	$R_{3,4,t} - R_{3,1,t}$	−0.1080*	0.1642*	0.0340	0.12
4	$R_{4,4,t} - R_{4,1,t}$	−0.1251*	0.0464*	−0.0036	0.04

This table provides the results from regressing the difference between the returns on most analysts and fewest analysts portfolios within each size quartile, on CRSP (NYAM-NASDAQ) value-weighted market returns. Here $\Sigma_{k=1}^{K} b_{o,k}$ refers to the sum of lagged betas, $\Sigma_{k=-1}^{-K} b_{o,k}$ refers to the sum of leading betas, and $b_{o,0}$ refers to the contemporaneous beta. * means significant at 1 percent level; † means significant at 5 percent level; * means significant at 10 percent level.

The sum of the lag coefficients is reliably negative for the two largest size quartiles for both 5 and 10 lags. For the smallest quartile, the lag sum in the 10-lag regression is negative but not significant. For the second size quartile the lag sum is positive in both cases and significant in the five lag regressions (as noted, this is not inconsistent with a slower speed of adjustment for portfolio *F* since $b_{o,0} > 0$). The analysis was repeated using the EWI and the results are reported in Table 5. Now the lag sum is negative in all cases and significant except in one, despite the fact that $b_{o,0}$ is positive (except for the largest size quartile, where the lag sum is significantly negative in any case). These results are generally consistent with portfolio *M*, showing a faster speed of adjustment to common information.

4.1 Lagged betas of individual securities

The results documented so far, based on our size-number of analysts-ranked portfolios, are consistent with the hypothesis that the prices of firms followed by fewer analysts adjust more slowly to common information for a given firm size. It is possible, however, that we have not controlled for the effect of other firm specific variables such as the volume of transactions. Controlling for firm-specific variables that may be related to the speed of price adjustment is particularly important in interpreting our evidence, given the analysis in Brennan (1990). Brennan (1990) suggests that the number of analysts following a particular stock may be determined by its speed of price adjustment to new information.[11] In this case the speed of adjustment is exoge-

[11] When the number of analysts is endogenously determined by the speed of adjustment as in Brennan (1990), the nature of the relation between 'these two variables is ambiguous. On the one hand,

Table 5
Regressions of arbitrage portfolio on equal-weighted index

Size	LHS	$\Sigma_{k=1}^{K} b_{0,k}$	$b_{0,0}$	$\Sigma_{k=-1}^{-K} b_{0,k}$	R^2
		A: 5 Leads/lags			
1	$R_{1,4,t} - R_{1,1,t}$	−0.0686*	0.1347*	−0.0044	0.02
2	$R_{2,4,t} - R_{2,1,t}$	−0.0138	0.1595*	0.0322‡	0.08
3	$R_{3,4,t} - R_{3,1,t}$	−0.1220*	0.1563*	0.0744*	0.07
4	$R_{4,4,t} - R_{4,1,t}$	−0.0821*	−0.0112	0.0248	0.01
		B: 10 Leads/lags			
1	$R_{1,4,t} - R_{1,1,t}$	−0.1245*	0.1359*	0.0022	0.03
2	$R_{2,4,t} - R_{2,1,t}$	−0.0753*	0.1615*	0.0430‡	0.08
3	$R_{3,4,t} - R_{3,1,t}$	−0.1689*	0.1564*	0.0817*	0.08
4	$R_{4,4,t} - R_{4,1,t}$	−0.0860*	−0.0097	0.0215	0.01

This table provides the results from regressing the difference between the returns on most analysts and fewest analysts portfolios within each size quartile on CRSP (NYAM-NASDAQ) equal-weighted market returns. Here $\Sigma_{k=1}^{K} b_{0,k}$ refers to the sum of lagged betas, $\Sigma_{k=-1}^{-K} b_{0,k}$ refers to the sum of leading betas, and $b_{0,0}$ refers to the contemporaneous beta. * means significant at 1 percent level; † means significant at 5 percent level; ‡ means significant at 10 percent level.

nously determined, and it is not affected by the number of analysts. By controlling for firm-specific factors such as size and turnover, we attempt to control for exogenous factors that affect the speed of price adjustment, If we find any relation between the speed of price adjustment and the number of analysts keeping these exogenous factors constant, then the results will provide stronger support for the speed of adjustment hypothesis than otherwise.

For each year from 1977 to 1988, regression (8) was estimated for individual securities in our sample that traded on the NYSE, AMEX, or NASDAQ, in order to estimate $LAG_{j,t}$. The following cross-sectional regressions were then run every year from 1977 to 1988:

$$LAG_{j,t} = a_{1,t} + a_{2,t}D_{j,t}^{\text{nasd}} + a_{3,t}\text{Ln } SZ_{j,t} + a_{4,t}(D_{j,t}^{\text{nyam}} \times \text{Ln } TO_{j,t}) + a_{5,t}(D_{j,t}^{\text{nasd}}\text{Ln } TO_{j,t}) + a_{6,t}ANALSYT_{j,t} + u_{j,t} \tag{12}$$

and

$$LEAD_{j,t} = \alpha_{1,t} + \alpha_{2,t}D_{j,t}^{\text{nasd}} + \alpha_{3,t}\text{Ln } SZ_{j,t} + \alpha_{4,t}(D_{j,t}^{\text{nyam}} \times \text{Ln } TO_{j,t}) + \alpha_{5,t}(D_{j,t}^{\text{nasd}}\text{Ln } TO_{j,t}) + \alpha_{6,t}ANALYST_{j,t} + u_{j,t}, \tag{13}$$

where the subscripts j and t refer to firm j and year t respectively. Ln SZ is the natural logarithm of the market value of equity (in billions of dollars) at the end of the previous year and Ln TO is the logarithm of the average daily share turnover, where daily share turnover is

when stocks respond slowly to new information, there is more scope for discovering mispricing; on the other hand, the reward for discovering mispricing is received sooner for more rapid price adjustments. These countervailing effects give rise to two possible equilibria: one in which many analysts collect information for stocks that respond rapidly to information, and the other in which many analysts collect information for stocks that respond slowly to information.

defined as the ratio of the number of shares traded per day to the number of shares outstanding at the end of the day. Since the product of firm size and share turnover is (approximately) equal to the value of shares traded, this formulation is roughly equivalent to one in which the logarithms of size and trading volume (instead of turnover) are included. The dummy variable $D^{nyam}_{j,t}$ ($D^{nasd}_{j,t}$) is assigned a value of 1 if firm j trades on NYSE or AMEX (NASDAQ) in year t, and 0 otherwise. Since NASDAQ is a dealership market, unlike NYSE and AMEX where orders are frequently crossed between investors, the trading volume on this market is not directly comparable to that on the other two markets. For this reason different turnover variables are used for stocks traded on NASDAQ and NYSE/AMEX.[12] *ANALYST* is the number of analysts following the firm at the end of the previous year. Thus, if the number of analysts following a firm increases its speed of adjustment to economywide information, we should expect the coefficient of *ANALYST* in Equation (12) to be negative.

The results of the annual regressions for five lags and leads are reported in Table 6.[13] The means and t-statistics of the coefficients from the annual regressions are reported at the foot of the table. The estimated coefficient of *ANALYST* in regression (12) is negative in every year but one,[14] consistent with the speed of adjustment hypothesis. The t-statistic on the mean coefficient of *ANALYST* is highly significant.

The slope coefficients on Ln *SZ* and Ln *TO* are both negative and reliably different from zero. Interestingly, for NYSE/AMEX stocks the coefficients of Ln *SZ* and Ln *TO* are insignificantly different from each other. This implies that if we had used the log of dollar volume as the independent variable in the place of Ln *SZ* and Ln *TO*,[15] there would be little change in the explanatory power of the regression. This result suggests that firm size affects the informativeness of the stock prices only through its effect on trading volume, as discussed by Admati and Pfleiderer (1988), and does not exert an independent influence. On the other hand, for NASDAQ firms the slope coefficient on Ln *TO* is significantly positive. A possible explanation for this result is that low-turnover firms on NASDAQ have systematically lower sensitivities to the VWI returns.

When the dependent variable is $LEAD_j$, the coefficients of both turnover variables are positive and statistically significant, suggesting

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[12] The NASDAQ stocks enter the sample only from 1983 for the tests here since their trading volume is not available on the CRSP prior to 1983.

[13] The results for 10 leads and lags were similar and hence not reported.

[14] For the 10-lag regressions, it is negative in 10 out of 12 years.

[15] Note that Ln *SZ* + Ln *TO* equals the log of dollar volume.

Table 6
Cross-sectional regressions of lead and lag betas (value-weighted market index) on firm size, turnover, and number of analysts for individual securities

Dep. var.	Sum of lag betas					Sum of lead betas					
YEAR	Ln *SZ*	Ln *TO* (NYAM)	Ln *TO* (NASD)	DUMMY (NASD)	*ANALYST*	Ln *SZ*	Ln *TO* (NYAM)	Ln *TO* (NASD)	DUMMY (NASD)	*ANALYST*	*n*
1977	−0.0549	−0.1423	—	—	−0.0096	0.0005	0.0592	—	—	0.0023	1359
1978	−0.1209	−0.1653	—	—	−0.0032	−0.0045	−0.0240	—	—	0.0039	1391
1979	−0.0939	−0.2177	—	—	0.0026	0.0252	0.0617	—	—	−0.0047	1371
1980	−0.0165	−0.1000	—	—	−0.0165	0.0114	−0.0435	—	—	0.0039	1343
1981	−0.0740	−0.0920	—	—	−0.0039	0.0106	0.0408	—	—	0.0004	1302
1982	−0.0185	−0.0825	—	—	−0.0128	−0.0022	0.0257	—	—	0.0013	1264
1983	−0.0965	−0.0887	0.0063	−0.0277	−0.0067	0.0461	0.1011	0.1313	0.0155	−0.0080	1684
1984	−0.0364	−0.0428	0.0798	0.0384	−0.0146	0.0291	0.0761	0.0761	0.0398	−0.0068	2045
1985	−0.0308	−0.0296	0.0362	0.1691	−0.0111	0.0054	0.0272	0.0736	0.0493	−0.0012	2222
1986	0.0298	−0.0071	0.0403	0.1091	−0.0124	0.0340	0.0503	0.0434	0.0493	−0.0060	2174
1987	−0.0701	0.0660	0.0177	0.1388	−0.0079	0.0275	0.0046	−0.0113	0.0657	0.0014	2288
1988	−0.0219	0.0018	0.0756	−0.0366	−0.0073	−0.0208	0.0204	0.0299	−0.0821	0.0021	2164
MEAN	−0.0504	−0.0750	0.0426	0.0744	−0.0086	0.0135	0.0333	0.0571	0.0229	−0.0010	
	(−4.10)	(−3.31)	(3.50)	(2.35)	(−5.53)	(2.44)	(2.81)	(2.89)	(1.04)	(−0.78)	

Crosssectional regressions of the sums of five lead and five lag betas on log size (Ln *SZ*), log turnover for NYAM firms (Ln *TO* (NYAM)), log turnover for NASDAQ firms (Ln *TO* (NASD)), dummy variable for NASDAQ firms (DUMMY (NASD)) and number of analysts *(ANALYST)*. The betas are obtained by regressing daily returns of each firm on lead and lag daily returns of CRSP (NYAM-NASDAQ) value-weighted index, each year. The summed betas are then regressed on Ln *SZ*, Ln *TO* (NYAM), Ln *TO* (NASD), and *ANALYST* The sample period is 1977-1988 for NYAM firms and 1983-1988 for NASDAQ firms. *n* refers to the number of firms in cross-sectional regressions. The numbers in parentheses are *t*-statistics.

Table 7
Cross-sectional regressions of lead and lag betas (equal-weighted market index) on firm size, turnover, and number of analysts for individual securities

Dep. Var.	Sum of lag betas					Sum of lead betas					
YEAR	Ln *SZ*	Ln *TO* (NYAM)	Ln *TO* (NASD)	DUMMY (NASD)	*ANALYST*	Ln *SZ*	Ln *TO* (NYAM)	Ln *TO* (NASD)	DUMMY (NASD)	*ANALYST*	*n*
1977	−0.1141	−0.4516	—	—	−0.0191	0.0119	0.1770	—	—	0.0033	1359
1978	−0.1088	−0.3686	—	—	0.0003	−0.0121	0.0004	—	—	0.0039	1391
1979	−0.0744	−0.3298	—	—	0.0052	0.0481	0.0933	—	—	−0.0036	1371
1980	−0.0441	−0.2569	—	—	−0.0059	0.0459	0.0471	—	—	0.0025	1343
1981	−0.1480	−0.2918	—	—	0.0110	0.0406	0.1327	—	—	−0.0032	1302
1982	−0.0672	−0.2719	—	—	−0.0145	0.0371	0.1210	—	—	0.0023	1264
1983	−0.1404	−0.2935	−0.2917	0.1419	−0.0023	0.0383	0.1612	0.1895	0.0250	−0.0050	1684
1984	−0.0753	−0.2255	−0.2690	0.1083	−0.0167	0.0642	0.1608	0.0949	0.0341	−0.0069	2045
1985	0.0529	−0.1616	−0.3112	0.5149	−0.0169	0.0064	0.0505	0.1037	−0.0174	0.0037	2222
1986	−0.0055	−0.0866	−0.1126	0.3240	−0.0136	0.0465	0.1039	0.0622	0.1343	−0.0047	2174
1987	0.0982	0.1067	−0.2255	0.3425	−0.0018	0.0354	0.0991	0.0490	0.0412	0.0040	2288
1988	0.0411	−0.0655	0.0168	−0.0698	−0.0171	0.0215	0.0420	0.0884	−0.1918	0.0032	2164
MEAN	−0.0808	0.2425	−0.1989	0.2269	0.0076	0.0284	0.0991	0.0980	0.0042	−0.0000	
	(−6.59)	(−7.09)	(−3.83)	(2.68)	(−2.62)	(3.75)	(6.22)	(4.86)	(0.10)	(−0.03)	

Cross sectional regressions of the sums of five lead and five lag betas on log size (Ln *SZ*), log turnover for NYAM firms (Ln *TO* (NYAM)), log turnover for NASDAQ firms (Ln *TO* (NASD)), dummy variable for NASDAQ firms (DUMMY (NASD)) and number of analysts (*ANALYST*). The betas are obtained by regressing daily returns of each firm on lead and lag daily returns of CRSP (NYAM NASDAQ) equal-weighted index, each year. The summed betas are then regressed on Ln *SZ*, Ln *TO* (NYAM), Ln *TO* (NASD), and *ANALYST*. The sample period is 1977–1988 for NYAM firms and 1983–1988 for NASDAQ firms. *n* refers to the number of firms in cross-sectional regressions. The numbers in parentheses are *t* statistics.

Table 8
Cross-sectional regressions of lag betas on firm size, turnover, and number of analysts for individual securities by exchange groups

	Dependent variable: lag beta with respect to the value-weighted index			Dependent variable: lag beta with respect to the equal-weighted index		
EXCH	Ln *SZ*	Ln *TO*	*ANALYST*	Ln *SZ*	Ln *TO*	*ANALYST*
NYSE	−0.0645	−0.0812	−0.0072	−0.0843	−0.2462	−0.0078
	(−4.50)	(−3.25)	(−4.74)	(−5.62)	(−6.40)	(−3.48)
AMEX	−0.0526	−0.0474	−0.0012	−0.0965	−0.2622	0.0025
	(−1.93)	(−1.69)	(−0.18)	(−2.45)	(−8.33)	(0.21)
NASDAQ	−0.0058	0.0365	−0.0119	−0.0655	−0.1782	−0.0240
	(−0.45)	(2.86)	(−2.70)	(−4.38)	(−3.75)	(−3.02)

Summary results from the cross-sectional regressions of the sums of five lag betas on log size (Ln *SZ*), log turnover Ln *TO*, and number of analysts *(ANALYST)* by exchange. The betas are obtained from time-series regressions of daily returns of each firm on lead and lag daily returns of CRSP (NYAM-NASDAQ) value-weighted and equal-weighted indices respectively, each year. The sample period is 1977-1988 for NYAM firms and 1983-1988 for NASDAQ firms. The number of firms in the cross-sectional regressions varies from 1062 to 1143 in NYSE, 191 to 2% in AMEX, and 468 to 1054 in NASDAQ. The numbers in parentheses are t-statistics.

that heavily traded firms tend to lead the value-weighted market index. On the other hand, the number of analysts variable is insignificant.

Table 7 reports the estimates of regressions (12) and (13) using security betas estimated with respect to the EWI. The results are qualitatively similar to that using the VWI, except that the slope coefficient of the NASDAQ turnover variable is now significantly negative .

4.2 Exchange groups

The effect of the number of analysts on the speed of adjustment may differ across markets because of the differences in the market structures, and disclosure and listing requirements. This subsection examines the relation between number of analysts and speed of adjustment separately in each of the three markets using regression (12).

Table 8 presents the means of the annual regression estimates for the three markets using lagged betas estimated with respect to the VWI and the EWI. The slope coefficients on *ANALYST* are significant for the NYSE and NASDAQ. Interestingly, the slope coefficient on *ANALYST* is larger in magnitude for NASDAQ than for NYSE or AMEX using both EWI and VWI lagged betas, which raises the possibility that investors may rely more on information provided by analysts for NASDAQ stocks than for exchange-listed stocks.

The *ANALYST* coefficient, however, is not significant for AMEX stocks. One possible explanation for this is that the variation in the number of analysts is small for AMEX stocks, which in turn will reduce the precision with which the slope coefficient on *ANALYST* is estimated.[16] In fact, the standard error of this slope coefficient is much larger for AMEX than for NYSE or NASDAQ.

The average number of analysts following AMEX firms is 2.16, which is smaller than the average number of analysts following NYSE and NASDAQ stocks (8.77 and 4.11 respectively). The evidence that the *ANALYST* coefficient is not significant for AMEX suggests the possibility that the effect of number of analysts on speed of response is nonlinear. We consider this possibility in the following section.

4.3 Nonlinear effect of number of analysts

Holden and Subrahmanyam argue that even a few analysts have a dramatic effect on the speed of adjustment, which suggests that there will be a convex relation between the number of analysts and the speed of adjustment. On the other hand, the AMEX evidence discussed suggests that a small number of analysts following a firm may not affect the speed of stock price response to information significantly.

To explore the possibility of a nonlinear effect of the number of analysts on the speed of adjustment, we fitted the regression

$$LAG_{j,t} = a_{1,t} + a_{2,t}D^{\text{nasd}}_{j,t} + a_{3,t}\text{Ln } SZ_{j,t} + a_{4,t}(D^{\text{nyam}}_{j,t} \times \text{Ln } TO_{j,t}) + a_{5,t}(D^{\text{nasd}}_{j,t}\text{Ln } TO_{j,t}) + \sum_{k=1}^{8} a_{k+5,t}D_{j,k,t} + u_{j,t}, \qquad (14)$$

where $D_{j,k,t}$ is a dummy variable that equals 1 if the number of analysts following the firm falls into group k, and 0 otherwise.[17] The mean of the annual coefficients from these regressions are reported in Table 9.

The results reveal a distinct nonlinear relation between the number of analysts and the speed of adjustment. The coefficient of the analyst dummy declines after the first analyst group (zero analysts) when lagged VWI betas are used to compute *LAG,,* but is then virtually flat or marginally increasing for the next five groups (up to 11 analysts) and then declines sharply. A similar nonlinear pattern emerges when LAG_j is computed using lagged EWI betas as well.[18]

This result suggests that the speed of adjustment is a nonlinear function of the number of analysts; few analysts have little effect, but once a threshold is reached an increase in the number of analysts

[16] The cross-sectional standard deviation of the number of analysts for the AMEX is 3.47, compared with that of 8.01 for the NYSE and 4.20 for NASDAQ.

[17] The groups, which were chosen to ensure a roughly equal number of firms in each, correspond to 0, 1, 2, 3-4, 5-7, 8-11, 12-15, and greater than 15 analysts.

[18] The coefficients on the analyst dummies are displaced downward in the regression with LAG, computed with the lagged EWI betas relative to that with lagged VWI betas. The reason is that the lagged EWI betas are on average smaller than the lagged VWI betas, since the EWI responds more slowly to common information than the VWI.

Table 9
Cross-sectional regressions of lag betas on firm size, turnover, and dummy variables for number of analysts

	MEAN	t-Statistics	Analysts
	A: Lagged betas with respect to value-weighted index		
Ln *SZ*	−0.0722	−5.29	
Ln *TO* (NYAM)	−0.0837	−3.72	
Ln *TO* (NASD)	0.0231	1.91	
DUMMY (NASD)	0.0785	2.24	
ANALYST 1	0.2103	1.53	0
ANALYST 2	0.1155	4.21	1
ANALYST 3	0.1465	4.92	2
ANALYST 4	0.1805	7.81	3.43
ANALYST 5	0.1865	6.80	5.92
ANALYST 6	0.1795	9.96	9.37
ANALYST 7	0.1237	6.96	13.42
ANALYST 8	0.0128	0.64	21.89
	B: Lagged betas with respect to equal-weighted index		
Ln *SZ*	−0.1002	−7.23	
Ln *TO* (NYAM)	−0.2492	−7.11	
Ln *TO* (NASD)	−0.2123	−4.01	
DUMMY (NASD)	0.2290	2.60	
ANALYST 1	−0.3275	−3.62	0
ANALYST 2	−0.3327	−7.70	1
ANALYST 3	−0.2997	−6.56	2
ANALYST 4	−0.2899	−7.37	3.43
ANALYST 5	−0.2717	−6.89	5.92
ANALYST 6	−0.2960	−7.74	9.37
ANALYST 7	−0.3499	−7.91	13.42
ANALYST 8	−0.4464	−7.45	21.89

Summary results from the cross-sectional regressions of the sums of five lag betas on log size (Ln *SZ*), log turnover for NYAM firms (Ln *TO* (NYAM)), log turnover for NASDAQ firms (Ln *TO* (NASD)), dummy variable for NASDAQ firms (DUMMY (NASDAQ)) and dummy variables for various analyst groups for all firms in CRSP. The dummy variables assume a value of 1 if the number of analysts for a firm belong to the corresponding *group* and 0 otherwise. There are eight groups based on the following grouping: 0, 1, 2, 3–4, 5–7, 8–11, 12–15, >15. The variables *ANALYST 1* to *ANALYST* 8 refer to the eight dummy variables corresponding to the eight groups. The betas are obtained from time-series regressions of daily returns of each firm on lead and lag daily returns of CRSP (NYAM-NASDAQ) value-weighted and equal-weighted indices respectively, each year. *ANALYSTS* refers to the mean number of analysts in the eight groups over 1977-1988. The sample period is 1977-1988 for NYAM firms and 1983-1988 for NASDAQ firms. The number of firms in these regressions vary between 1200 and 2300.

does increase the speed of adjustment. This is in contrast to the Holden and Subrahmanyam (1992) theory, in which even a few analysts have a dramatic effect on the speed of adjustment.

5. Conclusion

We have examined the empirical relation between the number of analysts following a firm and its speed of adjustment to new information that has common effects across firms. We found little effect of the number of analysts on the serial correlation of portfolio returns. However, Granger causality regressions revealed that the returns on many analyst firm portfolios tend to anticipate those on few analyst firm portfolios. Moreover, many analyst firm portfolios respond more rapidly to new information contained in returns on the value-weighted and the equal-weighted market indices. Examination of individual security returns shows a distinct nonlinear relation between the speed of adjustment and the number of analysts.

Appendix

As a preliminary to the proof of Proposition 1, note that the probability limits of the slope coefficients of the Granger causality regression **(3)** and (4) are given by

$$h_F = \frac{\operatorname{var}(R_M)\operatorname{cov}(R_{M,t}, R_{F,t-1}) - \operatorname{cov}(R_{M,t}, R_{F,t})\operatorname{cov}(R_{M,t}, R_{M,t-1})}{\operatorname{var}(R_M)\operatorname{var}(R_F) - [\operatorname{cov}(R_{M,t}, R_{F,t})]^2}, \quad \text{(A1)}$$

$$h_M = \frac{\operatorname{var}(R_F)\operatorname{cov}(R_{M,t}, R_{M,t-1}) - \operatorname{cov}(R_{M,t}, R_{F,t})\operatorname{cov}(R_{M,t}, R_{F,t-1})}{\operatorname{var}(R_M)\operatorname{var}(R_F) - [\operatorname{cov}(R_{M,t}, R_{F,t})]^2}, \quad \text{(A2)}$$

$$g_F = \frac{\operatorname{var}(R_M)\operatorname{cov}(R_{F,t}, R_{F,t-1}) - \operatorname{cov}(R_{M,t}, R_{F,t})\operatorname{cov}(R_{F,t} R_{M,t-1})}{\operatorname{var}(R_M)\operatorname{var}(R_F) - [\operatorname{cov}(R_{M,t}, R_{F,t})]^2}, \quad \text{(A3)}$$

$$g_M = \frac{\operatorname{var}(R_F)\operatorname{cov}(R_{F,t}, R_{M,t-1}) - \operatorname{cov}(R_{M,t}, R_{F,t})\operatorname{cov}(R_{F,t}, R_{F,t-1})}{\operatorname{var}(R_M)\operatorname{var}(R_F) - [\operatorname{cov}(R_{M,t}, R_{F,t})]^2}. \quad \text{(A4)}$$

Proof of Proposition la. Since the denominators in (A1) and (A4) are the same and positive, we need to compare only the numerators. Denote the numerator of each expression with the superscript n; hence, h_F^n denotes the numerator of h_F from (A1). From (1) and (A1),

$$\begin{aligned} h_F^n &= \left\{\sum_{k=1}^{K} \beta_{M,k}^2(1 + a_M^2) + \sigma^2\right\} a_M \sum_{k=1}^{K} \beta_{M,k}\beta_{F,k} \\ &\quad - \left\{\sum_{k=1}^{K} \beta_{M,k}\beta_{F,k}(1 + a_M a_F)\right\} a_M \sum_{k=1}^{K} \beta_{M,k}^2 \\ &= \sigma^2 a_M \sum_{k=1}^{K} \beta_{M,k}\beta_{F,k} + a_M^2(a_M - a_F) \sum_{j=1}^{K} \sum_{k=1}^{k} \beta_{M,j}^2\beta_{M,k}\beta_{F,k}. \end{aligned} \quad \text{(A5)}$$

Using similar steps we get

$$g_M^n = \sigma^2 a_F \sum_{k=1}^{K} \beta_{M,k}\beta_{F,k} + a_F^2(a_F - a_M) \sum_{j=1}^{K} \sum_{k=1}^{K} \beta_{F,j}^2\beta_{M,k}\beta_{F,k}. \quad \text{(A6)}$$

Since $a_F > a_M$, the first term in (A6) is greater than the first term in (A5), and the second term in (A6) is positive while that in (A5) is negative. It follows that $g_M > h_F$ In fact, from (A5), it can be seen that if the variance of the idiosyncratic component of return (σ^2) is sufficiently small, then h_F would be negative.

Proof of Proposition 1b. If $\beta_{M,k}(1 + a_M) = \beta_{F,k}(1 + a_F)$ for all k and $a_F > a_M$, then $\beta_{M,k} > \beta_{F,k}$ and $\beta_{M,k}a_M < \beta_{F,k}a_F$. Some algebraic manipulations of the numerators of (A2) and (A1) yields

$$b_M^n - b_F^n = \sigma^2 a_M \sum_{k=1}^{K} (\beta_{M,k}^2 - \beta_{M,k}\beta_{F,k})$$

$$+ a_M(1 + a_M a_F) \sum_{k=1}^{K} \beta_{M,k}\beta_{F,k}\left\{\sum_{j=1}^{K} \beta_{M,j}^2 - \sum_{j=1}^{K} \beta_{M,j}\beta_{F,j}\right\}$$

$$+ \sum_{i=1}^{K} \beta_{M,i}^2 \sum_{j=1}^{K} \beta_{F,j} \sum_{k=1}^{K} (a_F\beta_{F,k} - a_M\beta_{M,k}).$$

Now, $b_M^n > b_F^n$ since each of the three terms in this expression is positive. The proof that $g_M > g_F$ is similar.

References

Admari, A., and P. Pfleiderer, 1988, “A Theory of Intraday Patterns: Volume and Price Variability,” *Review of Financial Studies,* 1, 3-40.

Arbel, S. C., and P. Strebel, 1983, “Giraffes, Institutions and Neglected Firms,” *Financial Analysts Journal,* 39, 57-63.

Bhushan, R., 1989, “Firm Characteristics and Analyst Following,” *Journal of Accounting and Economics,* 11, 255-274.

Brennan, M. J., 1990, “Presidential Address: Latent Assets,” *Journal of Finance,* 45, 709-730

Brennan, M. J., and P. J. Hughes, 1991, “Stock Prices and the Supply of Information,” *Journal of Finance,* 46, 1665-1691.

Fama, E. F., and J. D. MacBeth, 1973, “Risk, Return and Equilibrium: Empirical Tests,” *Journal of Political Economy,* 81, 607-636.

Foster, F. D., and S. Viswanathan, 1993, “The Effect of Public Information and Competition on Trading Volume and Price Volatility.” *Review of Financial Studies,* 6, 23-56.

Granger, C. W. J., 1969, “Investigating Causal Relations by Econometric Models and Cross-Spectral Models,” *Econometrica,* 37, 424-438.

Holden, C., and A. Subrahmanyam, 1992, “Long-Lived Private Information and Imperfect Competition,” *Journal of Finance,* 47, 247-270.

Kyle, A. S., 1985, “Continuous Auctions and Insider Trading,” *Econometrica, 53,* 1315-1335.

Lo, A., and C. MacKinlay, 1988, “Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test,” *Review of Financial Studies,* 1, 175-206.

Lo, A., and C. MacKinlay, 1990, "'When Are Contrarian Profits due to Stock Market Overreaction," *Review of Financial Studies,* 3, 175-206.

Metton, R. C., 1987, "A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance,* 42, 483-510.

Sims, C. A., 1972, "Money, Income and Causality," *American Economic Review,* 62, 540-552.