Why Does Aggregate Insider Trading Predict Future Stock Returns

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WHY DOES AGGREGATE INSIDER TRADING PREDICT FUTURE STOCK RETURNS?*

H. NEJAT SEYHUN

This paper documents that, for the period from 1975 to 1989, the aggregate net number of open market purchases and sales by corporate insiders in their own firms predicts up to 60 percent of the variation in one-year-ahead aggregate stock returns. This study also examines whether the ability of aggregate insider trading to predict future stock returns can be attributed to changes in business conditions or movements away from fundamentals. Evidence suggests that both explanations contribute to the predictive ability of aggregate insider trading.

I. INTRODUCTION

Numerous studies in finance document the time-varying and predictable nature of stock returns [Fama and Schwert, 1977; Fama, 1981; Keim and Stambaugh, 1986]. Using a long horizon of past returns, Fama and French [1988a] find that approximately 25 to 40 percent of the variation in three- to five-year future stock returns can be predicted. Fama and French [1988b] show that future stock returns can also be forecast using dividend price ratios. Two basic issues, however, remain unresolved in this literature. First, confidence intervals for forecast returns are large, which suggests that much of the forecastability may not be real [Richardson, 1989; Hodrick, 1990; Nelson and Kim, 1990]. Second, it is not clear whether the predictable variations in stock returns represent rational assessments of varying required returns or persistent swings from fundamental values as a result of noise trading [Fama, 1991].[1]

Fama and French [1989] and Chen [1991] assert that predictability of stock returns is a rational response to variations in expected future investment and consumption opportunities. For instance, when the expected future state of the economy is strong,

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1. Other studies that examine the time variation in expected stock returns include Merton [1980], DeBondt and Thaler [1985, 1987], Gibbons and Ferson [1985], French and Roll [1986], Chan [1988], Lo and MacKinlay [1988], and Poterba and Summers [1988].

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attempts to smooth consumption by borrowing against the future output will raise the long rates of interest. Similarly, when the expected future state of the economy is strong, expected return on risky investments will also have to be higher to induce investors to forgo consumption in favor of profitable risky investments. Hence, changes in business conditions produce time-varying expected stock returns.[2]

A competing hypothesis states that stock prices are affected by the trading activities of both informed and uninformed traders and, consequently, can diverge from fundamental values [Shiller, 1984; De Long and others, 1989, 1990a,b]. According to this view, noise traders can at times react to current fads and push prices away from fundamental values. Over longer horizons, however, prices tend to revert closer to fundamental values. Hence, the fads hypothesis predicts that the stock prices can contain predictable, irrational, mean-reverting components.

This study provides new evidence on the degree to which stock returns are forecastable. Seyhun [1988a] reports that aggregate insider trading is positively related to future market returns over the 1975 to 1981 period. Insider trading refers to the number and volume of open market sales and purchases by officers, directors, and large shareholders in their own firms. Aggregate insider trading refers to the sum of insider transactions at each point in time across all public firms. This study extends the evidence on the predictive ability of aggregate insider trading by examining the forecasting ability of multimonth aggregate insider trading and the relations between aggregate insider trading and variables that are associated with business conditions and fundamental values.

The multimonth aggregate insider trading data provide the strongest evidence to date on the predictability of future stock returns. From 1975 to 1989 the twelve-month aggregate net number of transactions by insiders in over 9000 firms predicts up to 25 percent of the variations in future six-month-ahead stock returns and 60 percent of the variations in one-year-ahead stock returns. Aggregate insider trading in small firms also predicts future stock returns in larger firms. Predictability increases with the length of forecasting horizon, months of past insider trading,

2. Also see the intertemporal asset pricing model of Cox, Ingersoll, and Ross [1985] for a formal relation between productivity of capital and expected market premium.

and market sensitivity of the stocks and significantly exceeds the predictive ability of past stock returns or dividend yields. For instance, dividend yields predict 5 to 7 percent of the variation in one-year-ahead stock returns [Fama and French, 1988b].

Evidence provided in this study also suggests that changes in business conditions contribute to the forecasting ability of aggregate insider trading since aggregate insider trading is positively related to changes in future real activity as measured by corporate cash flows, Index of Industrial Production, and Gross National Product. However, not all predictive ability can be attributed to business conditions. Including variables such as changes in future cash flows, Index of Industrial Production, and Gross National Product as additional predictors of stock returns does not eliminate the predictive ability of aggregate insider trading. Also, variables that are related to expected future real activity such as dividend yield, term spread, and default spreads do not attenuate the predictive ability of insider trading.

Cross-sectional tests using market risk, past stock returns, and firm size also corroborate the finding that aggregate insider trading is a separate predictor of future stock returns. Once again, the predictive ability of aggregate insider trading is maintained when market risk, firm size, and past stock returns are used as additional predictors of future stock returns. Also, the predictive ability of aggregate insider trading exceeds that of market risk, past stock returns, and firm size.

Simple predictive tests cannot reject the hypothesis that aggregate insider trading can be used to identify periods when current prices and fundamental values diverge. First, using signals from past aggregate insider trading, future stock returns on portfolios containing a large number of firms can be predicted to be negative. This finding casts doubt on the view that all predictive ability of aggregate insider trading can be attributed to business conditions. Second, the magnitude of the predicted returns (both positive and negative) is large and likely to be economically significant.

The remainder of the paper is organized as follows. Section II contains a description of the tests to separate the reasons for the predictive ability of aggregate insider trading. Data sources and sample characteristics are reported in Section III, followed by the empirical findings in Section IV, and conclusions in Section V.

II. The Information Content of Aggregate Insider Trading

Seyhun [1988a] is the first study that documents a positive relation between past aggregate insider trading and future stock returns.[3] Aggregate stock prices rise following increases in aggregate insider purchases and fall following increases in aggregate insider sales. Moreover, the forecasting ability of aggregate insider trading increases with the market risk of the firms. Overall evidence suggests that the information content of aggregate insider trading results from changes in economywide factors not yet reflected in firms' stock prices. However, Seyhun [1988a] does not identify the economywide factors that lead to the predictive ability of aggregate insider trading.

This study examines two competing hypotheses that predict a positive relation between aggregate insider trading and future stock returns: (i) the cash flow hypothesis and (ii) the fads hypothesis. The cash flow hypothesis postulates that corporate insiders can predict the future cash flows in their own firms before other market participants. To the extent that the changes in cash flows are due to the future economywide activity, insiders in all firms will also observe similar signals in their own firms and also trade in their own firms in the same direction. After a while, as changes in economywide cash flows become recognized by other market participants, stock prices of all firms will tend to adjust. Hence, aggregate insider trading will predict the future real activity and future stock returns.

To test the contribution of the cash flow hypothesis, correlations of aggregate insider trading with future growth rates of after-tax corporate cash flows, Index of Industrial Production, and Gross National Product are examined. The cash flow hypothesis predicts positive relation between aggregate insider trading and variables that measure future real activity. Second, studies have shown that dividend yield, and term and default spreads are related to expected future real activity [Fama and French, 1989; Chen, 1991]. Hence, current insider trading activity should be related to current dividend yield, term spread, and default spreads. Moreover, the ability of aggregate insider trading to predict the future stock returns should be attenuated when dividend yield, and term and default spreads are included as additional explanatory vari-

3. See Lorie and Niederhoffer [1968], Jaffe [1974], and Seyhun [1986] for relations between insider trading and firm-specific future price movements.

ables since they capture the same predictable component of future stock returns.

The fads hypothesis implies that stock prices can deviate away from fundamental values. Insiders are expected to realize that current prices differ from fundamentals since they would be knowledgeable about the fundamentals and they can observe the current prices. If the mispricing is marketwide, then aggregate insider trading will predict future market returns. When current prices are too low, insiders in aggregate will buy stock. When current prices are too high, insiders in aggregate will sell stock. On the other hand, if mispricing is firm specific, then insiders' transactions in each firm will cancel out, and aggregate insider trading should not forecast future market returns.

The fads hypothesis also predicts that current aggregate insider trading will predict future stock returns. Moreover, the fads hypothesis uniquely predicts that insiders will be able to predict not only when future stock returns are high but also when future stock returns are expected to be *negative.* If a current fad pushes stock prices too high, there will be a subsequent decline in prices when the fundamentals influence the pricing. In contrast, the business cycle explanations predict a low positive but not negative, expected future returns when the current state of the economy is strong or when future investment opportunities are weak. Second, the fads hypothesis predicts that the predictive ability of aggregate insider trading should not be eliminated when additional predictors of time variation in stock returns such as past stock returns, dividend yields, term spread, and default spread are included since they capture separate components of future stock returns. Similarly, predictors of cross-sectional variation in stock returns such as firm size and market risk should also not attenuate the predictive power of aggregate insider trading.

III. Data and Sample Characteristics

A. Data

The insider trading data analyzed in this study are obtained from a computer tape compiled by the Securities and Exchange Commission (SEC). The tape contains all insider trading in publicly held firms from January 1975 to December 1989. This study includes only open market sale and purchase transactions. Other transactions such as private transactions, option exercises, and shares acquired through a plan are excluded since these transactions are less likely to be motivated by information reasons. Also, amended and inconsistent transactions are omitted from the sample. The overall sample contains data on 19,571 firms. A subsample of insider transactions in 9103 firms trading on the New York Stock Exchange, American Stock Exchange, and Over The Counter, also present on the files of the Center for Research in Security Prices (CRSP) of the University of Chicago, are analyzed separately.

The data on stock returns are obtained from the CRSP tapes. The dividend yield is computed from the CRSP tapes for the value-weighted CRSP index. Quarterly data on Gross National Product, and after-tax corporate cash flows, and monthly data on Index of Industrial Production are obtained from the Citibase data files. The definitions of term and default spreads follow those of Fama and French [1989]. The data on term spread are obtained from the CRSP bond files and Ibbotson and Sinquefield bond files and measured as the difference between Aaa bond portfolio and one-month Treasury Bill yields. The data on default spread are obtained from the Ibbotson and Sinquefield bond files and measured as the difference between low-grade and high-grade corporate bond yields. The data on default spread and term spread are available from January 1975 to December 1987.

B. Sample Characteristics of Insiders' Transactions

Sample characteristics of insiders' transactions are shown in Table I. Panel A of Table I shows that the overall sample contains 426,804 purchases and 417,603 sales by insiders in 19,571 firms. The average number of shares purchased equals 8727.6, and the average number of shares sold equals 13,437.4. Consequently, the overall sample contains trades involving 9.3 billion shares.

Panel B of Table I groups insiders' transactions into firm size quintiles for a subsample of 9103 firms listed on the CRSP tapes. The sample contains a wide range of firms: average firm size in the smallest quintile equals $3.9 million, increasing to $1.5 billion in the largest quintile. Panel B shows that aggregate insider trading increases by firm size. There are 41,740 transactions in the smallest quintile group, increasing uniformly to 224,439 transactions in the largest quintile. The number of shares traded per transaction also increases from 10,428.5 in the smallest quintile to 15,680.4 in the largest quintile. However, proportionately, insiders are more active in smaller firms: for the sample period examined,

TABLE I

SAMPLE CHARACTERISTICS OF INSIDERS' TRANSACTIONS FROM JANUARY 1975 TO DECEMBER 1989[a]

Panel A: Overall sample

Number of purchases	Number of sales	Average shares purchased	Average shares sold	Number of firms
426,804	417,603	8,727.6	13,437.4	19,571

Panel B: Insider trading by quintile groups

	Group 1 (small firms)	Group 2	Group 3	Group 4	Group 5 (large firms)
Number of purchases	25,623	40,445	51,058	65,584	88,601
Number of sales	16,117	32,727	46,338	70,123	135,838
Number of transactions	41,740	73,172	97,396	135,707	224,439
Average shares purchased	7,110	4,841.3	5,012.2	6,471.4	17,161.8
Average shares sold	15,704.2	13,952.5	9,551.6	10,223.8	14,714.1
Average shares traded	10,428.5	8,916.4	7,171.9	8,410.4	15,680.4
Proportion of firm traded	0.020	0.015	0.017	0.015	0.010
Firm value (million)	\$3.9	\$12.0	\$30.1	\$85.0	\$1,453.9
Number of firms	1820	1821	1821	1821	1820

Panel C: Time series characteristics of monthly aggregate net number of transactions, ANT, from January 1975 to December 1989 by quintile groups and all firms

	Group 1 (small firms)	Group 2	Group 3	Group 4	Group 5 (large firms)	All firms
Mean	47.3	37.2	19.4	−33.9	−269.4	−5.05
σ	75.6	101.5	139.4	186.3	310.5	1027.3
Max	351	285	440	590	805	2849
Min	−226	−305	−377	−563	−1103	−3224
r_1	0.70	0.65	0.69	0.68	0.55	0.70
r_2	0.51	0.45	0.46	0.48	0.30	0.48
r_3	0.49	0.33	0.27	0.34	0.27	0.37
r_{12}	0.28	0.08	0.03	0.08	0.05	0.07

[a] The averages in Panels A and B are per transaction. In Panel C the term σ denotes standard deviation, and the term r_k denotes the serial correlation coefficient of ANT at lag k. All firms in Panel C contains the overall sample of 19,571 firms.

insiders trade 2 percent of the outstanding shares per year in the smallest quintile compared with 1 percent in the largest quintile.

C. Aggregate Insider Trading Activity

The insider trading used in this study is computed by aggregating corporate insiders' (officers, directors, and owners of 10 percent or more of equity) transactions across firms. The net number of transactions in firm i and month t, $NT_{i,t}$, is defined as follows:

$$NT_{i,t} = \sum_{j=1}^{N} H_{j,i,t}, \tag{1}$$

where N denotes the number of open market sales and purchases by insiders in firm i and month t, $H_{j,i,t}$ equals 1 if transaction j is a purchase and -1 if transaction j is a sale. The aggregate net number of transactions by insiders in each month t and group k, ANT_t^k, is computed by summing the net number of transactions across firms:

$$ANT_t^k = \sum_{i=1}^{K} NT_{i,t}, \qquad k = 1 \text{ to } 5 \text{ and ALL firms}, \tag{2}$$

where K denotes the number of firms in group k (either quintiles of firm size or all firms).

Additional measures of insider trading are computed. The aggregate net number of shares traded by insiders in month t and group k, ANS_t^k, is defined by multiplying $H_{j,i,t}$ in equation (1) by the number of shares traded to compute $NS_{i,t}$ and again summing in equation (2) to compute ANS_t^k. The ANS_t^k measure puts equal weight on each share traded and hence favors large transactions proportionately. The empirical results using ANS are qualitatively similar, although smaller in magnitude, since the information content of insiders' transactions does not increase linearly with the number of shares traded. Additional standardized measures of insider trading are computed for each firm i by netting out the mean and dividing by the sample standard deviation of $NT_{i,t}$ and $NS_{i,t}$ in equation (1) and again summing in equation (2). These measures are denoted $SANT$ and $SANS$ and provide similar, although slightly less significant, results.

Panel C of Table I shows the time series characteristics of ANT_t^k for quintile groups and all firms. ANT_t^{ALL} is also plotted in Figure I. ANT_t^{ALL} appears to be a slow-moving, positively corre-

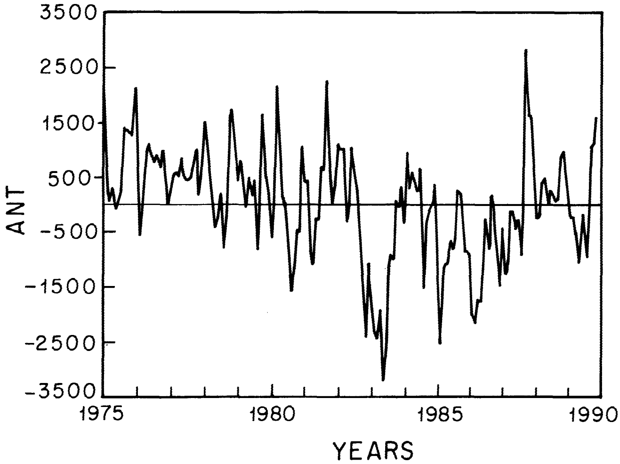

FIGURE I
Monthly Aggregate Net Number of Transactions, *ANT*, by All Insiders in 19,571 Firms from January 1975 to December 1990

lated, mean-stationary series. There are no dominating outliers in the series.

For the three largest firm quintiles and the overall sample, the maximum net purchase activity shown in Panel C of Table I occurs in October 1987. Moreover, the sample maximum is more than two standard deviations away from the sample means (see Seyhun [1990] for analysis of insider trading around the Crash of October 1987). For the two smallest quintile groups the largest net purchase activity occurs in December 1975 and December 1978, respectively (Seyhun [1988b] examines relations between insider trading and January effect in small firms). For all but two of the groups, the largest net sale activity occurs in May 1983.

Panel C of Table I also shows the serial correlation coefficients of *ANT*. The pattern of geometric decay suggests first-order autoregressive models (AR(1)). Simple AR(1) models provide good fits as judged by insignificant Box-Pierce-Q statistics for all except ANT^1, which requires a third-order autoregressive model. Hence, *ANT* series appear to be stationary.

Both hypotheses tested in this study imply that insiders in different firms respond to economywide factors by trading their own firms' stock. These factors are future real activity or movements of prices away from fundamentals. Consequently, both hypotheses predict that insider trading ought to be correlated across firms. Moreover, insider trading in firms with high market risk ought to be more closely correlated since by definition these firms are more sensitive to economywide factors.

While not shown here, cross correlations of aggregate insider trading for firm size quintiles and market risk quintiles are examined [Seyhun, 1988a]. With both classifications aggregate insider trading is positively correlated across groups. The typical cross-correlation coefficient is approximately 0.8. Insider trading in firms that are similar in size is even more positively correlated. Similarly, cross correlations of insider trading in smaller size firms and higher risk firms are greater. Also, time aggregation of insider trading increases the cross correlations of all groups. Overall, this evidence suggests that movements in economywide factors do affect insider trading patterns.

IV. Empirical Results

A. Time Series Tests

The tests shown in Table II measure the extent to which multimonth aggregate insider trading predicts future excess stock returns. The dependent variables are future one-month, three-month, six-month, and twelve-month excess stock returns, defined as the difference between continuously compounded monthly stock returns and the return on one-month Treasury Bills, summed over the forecasting horizon. The excess returns are computed using *nonoverlapping* periods for firm size quintiles, all firms in the sample and the equally weighted and value-weighted market indices. The independent variables in the regressions shown in Table II are the past three-month *ANT* in Panel A and *ANS* in Panel B. Using *SANT* and *SANS* measures yields similar findings.

Some of the regressions shown in Table II exhibit serially correlated residuals. In these cases the residuals are fitted with a simple AR(1) or AR(2) model to take the serial correlation to account. The adjusted R^2s are obtained from simple ordinary least squares regressions.

Table II shows limited forecasting ability for three-month aggregate insider trading. In both Panels A and B aggregate insider trading forecasts future returns to the two smallest quintiles. There is also some marginal predictive ability for the returns to the third quintile, the equally weighted index, and the overall sample. Using the aggregate net number of shares, *ANS*, yields more noisy

TABLE II

Time Series Regression of Future Excess Stock Returns on Past Three-Month Aggregate Insider Trading Activity by Firm Size Quintiles and All Firms[a]

	Panel A: $\sum_{k=t}^{t+m-1} (R_k^i - R_k^f) = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} ANT_k^j$									Panel B: $\sum_{k=t}^{t+m-1} (R_k^i - R_k^f) = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} ANS_k^j$							
	$n = 3$, $m = 1$		$n = 3$, $m = 3$		$n = 3$, $m = 6$		$n = 3$, $m = 12$			$n = 3$, $m = 1$		$n = 3$, $m = 3$		$n = 3$, $m = 6$		$n = 3$, $m = 12$	
(i,j)	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	$(*i,j)$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$
1,1	9.09	0.061	25.92	0.155	47.69	0.276	74.45	0.444	1,1	1.82	0.009	8.02	0.052	18.84	0.108	−26.05	0.031
	(3.27)		(3.41)		(3.41)		(3.37)			(1.43)		(2.04)		(2.09)		(−1.19)	
2,2	6.38	0.032	14.31	0.072	27.43	0.140	31.57	0.111	2,2	0.88	0.006	5.17	0.010	18.17	0.145	23.24	0.211
	(2.91)		(2.34)		(2.36)		(1.62)			(1.22)		(1.25)		(2.40)		(2.12)	
3,3	2.31	0.007	6.04	0.014	13.48	0.059	10.54	−0.026	3,3	0.66	0.000	2.99	0.002	2.43	−0.030	25.82	0.204
	(1.54)		(1.35)		(1.66)		(0.82)			(0.75)		(1.06)		(0.44)		(2.08)	
4,4	1.12	0.004	3.82	0.013	7.26	0.031	7.37	0.004	4,4	0.71	0.002	2.66	0.006	5.81	0.033	9.74	0.119
	(1.11)		(1.33)		(1.38)		(1.02)			(0.96)		(1.17)		(1.39)		(1.66)	
5,5	0.31	−0.004	0.49	−0.016	0.81	−0.034	2.08	−0.050	5,5	−0.02	−0.006	−0.09	−0.016	0.11	−0.035	−0.52	−0.039
	(0.61)		(0.31)		(0.27)		(0.62)			(−0.23)		(−0.31)		(0.26)		(−0.72)	
E,A	0.25	0.011	0.62	0.015	1.09	0.029	1.00	0.051	E,A	0.02	−0.005	0.13	−0.010	0.42	0.033	0.46	−0.071
	(1.72)		(1.36)		(1.36)		(1.50)			(0.25)		(0.64)		(1.40)		(1.46)	
V,A	0.08	−0.004	0.13	−0.016	0.39	−0.025	0.74	−0.043	V,A	−0.04	−0.003	−0.05	−0.016	0.10	−0.032	−0.28	−0.067
	(0.61)		(0.33)		(0.56)		(0.68)			(−0.69)		(−0.30)		(0.36)		(−0.43)	
A,A	0.30	0.007	0.95	0.026	1.69	0.059	2.01	0.062	A,A	0.05	−0.003	0.26	0.003	0.72	0.074	1.31	−0.019
	(1.61)		(1.80)		(1.66)		(1.36)			(0.59)		(1.09)		(2.11)		(1.64)	
N	177		59		29		14		N	177		59		29		14	

a. The sample period is 180 months from January 1975 to December 1989. The terms R_k^i, $i = 1, \ldots, 5$,E,V,A denotes the continuously compounded returns in month t for the quintiles of firm sizes, equally and value-weighted market indices, and all firms in the sample respectively. R_k^f denotes the continuously compounded return on one-month Treasury Bills in month t. $ANT^i, j = 1, \ldots, 5$,A denotes the aggregate net number of transactions by insiders for the quintiles of firm sizes and all firms, respectively. $ANS^j\ j = 1, \ldots, 5$,A denotes the aggregate net number of shares traded by insiders for the quintiles of firm sizes and all firms, respectively. All estimated regression coefficients are multiplied by 10^5 in Panel A,and 10^9 in Panel B. The t-statistics are in parentheses. The adjusted R^2 are from ordinary least squares regressions. N denotes the number of observations in the regressions.

forecasts than the aggregate net number of transactions, *ANT*. To interpret the coefficient estimates, consider the six-month-ahead forecasts in the smallest quintile in Panel A. If insiders increase their net purchases by one standard deviation, then the one-month-ahead stock returns are expected to be 9.5 percent higher than average (estimated coefficient of 0.0004769 times standard deviation of 200.1). Hence, forecast magnitudes are economically significant.[4]

Table III uses twelve months to compute aggregate insider trading. If aggregation over time smooths out the variations in the aggregate insider trading that are not related to future stock returns, then the use of longer horizons to measure aggregate insider trading should lead to increased forecasting ability. Consequently, the results in Table III are expected to be more significant than those in Table II.

Table III, Panel A, shows highly significant forecasting ability of aggregate insider trading for all horizons examined. For the one-month-ahead forecasting horizon, the adjusted R^2 values vary from zero to 8 percent. The adjusted R^2 values also increase uniformly with an increasing forecast horizon. To interpret the coefficient estimates, again consider the six-month-ahead forecasting horizon for the smallest quintile. If insiders increase their net number of purchases by one standard deviation, then the six-month-ahead forecast stock returns would be 11 percent higher than average (estimated coefficient of 0.0001571 times the standard deviation of 710.8).

The last column of Table III, Panel A, uses past twelve-month aggregate insider trading to forecast the twelve-month-ahead excess returns. The adjusted R^2 values in the last column reach over 60 percent. For the smallest quintile the coefficient estimate is 0.0002294, with a t-statistic of 4.55. When insiders increase their net purchases by one standard deviation, excess returns are predicted to be 16.3 percent more than average (0.0002294 times

4. As a test of the sensitivity to the market Crash of 1987, all data from January 1987 through December 1989 are deleted. The results are qualitatively similar. Hence, the findings reported here cannot be attributed to the market Crash of 1987. As an additional test of the empirical methodology, a test variable is constructed that has stochastic characteristics similar to those of the aggregate insider trading variable. Specifically, the test variable is an AR(1) series with an autocorrelation coefficient of 0.70 and normally distributed innovations (Table I, Panel C). Repeating the tests in Table II to IV with the test variable yields no relations between future stock returns and the test variable. This finding further suggests that the significant findings arise from the economic content of the aggregate insider trading rather than methodological deficiencies.

TABLE III

Time Series Regression of Future Excess Stock Returns on Past Three-Month Aggregate Insider Trading Activity by Firm Size Quintiles and All Firms[a]

Panel A: $\sum_{k=f}^{t+m-1}(R_k^i - R_k^f) = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} ANT_k^j$

Panel B: $\sum_{k=t}^{t+m-1}(R_k^i - R_k^f) = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} ANS_k^j$

	Panel A: $n = 12$, $m = 1$		$n = 12$, $m = 3$		$n = 12$, $m = 6$		$n = 12$, $m = 12$			Panel B: $n = 12$, $m = 1$		$n = 12$, $m = 3$		$n = 12$, $m = 6$		$n = 12$, $m = 12$	
(i,j)	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	(i,j)	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$
1,1	2.76	0.080	7.94	0.154	15.71	0.260	22.94	0.603	1,1	1.55	0.026	5.19	0.057	11.18	0.087	14.39	0.096
	(3.34)		(3.32)		(4.08)		(4.55)			(1.89)		(2.09)		(1.89)		(1.54)	
2,2	1.91	0.045	5.49	0.093	12.91	0.239	21.05	0.612	2,2	1.04	0.051	3.65	0.094	8.52	0.238	12.13	0.565
	(2.65)		(2.58)		(3.08)		(4.64)			(2.70)		(2.59)		(3.07)		(4.23)	
3,3	1.03	0.021	3.09	0.045	7.38	0.145	14.01	0.531	3,3	0.50	0.010	1.57	0.023	3.14	0.048	10.13	0.542
	(1.93)		(1.90)		(2.36)		(3.97)			(1.49)		(1.52)		(1.54)		(7.70)	
4,4	0.57	0.013	1.80	0.036	4.10	0.111	8.26	0.505	4,4	0.40	0.012	1.26	0.029	2.86	0.096	5.16	0.520
	(1.66)		(1.75)		(2.09)		(3.78)			(1.59)		(1.62)		(1.96)		(4.63)	
5.5	0.15	−0.002	0.44	−0.007	1.21	0.013	2.75	0.237	5,5	0.00	−0.006	0.02	−0.018	0.03	−0.037	0.19	−0.060
	(0.81)		(0.79)		(1.17)		(2.25)			(−0.10)		(−0.11)		(0.12)		(1.45)	
E,A	0.08	0.009	0.23	0.023	0.53	0.090	0.96	0.372	E,A	0.02	−0.002	0.06	−0.005	0.16	0.010	0.22	0.132
	(1.59)		(1.51)		(1.91)		(2.95)			(0.79)		(0.86)		(1.13)		(2.71)	
V,A	0.03	−0.003	0.10	−0.007	0.27	0.006	0.38	−0.007	V,A	−0.01	−0.005	−0.03	−0.015	−0.02	−0.037	−0.05	−0.079
	(0.77)		(0.79)		(1.08)		(0.95)			(−0.59)		(−0.41)		(−0.16)		(−0.23)	
A,A	0.13	0.025	0.38	0.059	0.87	0.161	1.62	0.610	A,A	0.04	0.013	0.15	0.030	0.32	0.075	0.69	0.356
	(2.09)		(2.11)		(2.49)		(4.62)			(1.56)		(1.64)		(1.79)		(2.86)	
N	168		56		28		14		N	168		56		28		14	

a. See note to Table II.

the standard deviation of 710.8). Also, the results for the twelve-month-ahead excess returns in the last column of Table III indicate that (i) neither the use of the overlapping independent variables nor (ii) seasonalities in stock returns or insider trading are responsible for the significant findings in Tables II and III.

Aggregate insider trading forecasts not only the future returns to the five size quintiles, but also all firms and the equally weighted CRSP index. Only the value-weighted index does not exhibit significant forecastability. The results in Panel A of Table III suggest that the forecasting ability of *ANT* decreases with increasing firm size.

Panel B of Table III uses the aggregate net number of shares traded, *ANS*, to forecast future stock returns. These results are generally similar to those in Panel A, although the significance levels are somewhat smaller. The maximum adjusted R^2 in Panel B is about 56 percent. The lack of monotonic results using *ANS* is due to the fact that the most informed traders are top executives and insiders in small firms who trade relatively few shares. In contrast, institutional shareholders in large firms trade much larger volumes on less information. Consequently, information content of insiders' transactions does not increase monotonically with shares traded [Seyhun, 1986].

Table IV groups insiders' transactions by market risk quintiles instead of size quintiles. Market risk is defined as the beta coefficient from market model regression. In each year individual security returns are regressed against the value-weighted market returns using 36 months of prior and 36 months of subsequent monthly data. Estimated beta coefficients are then averaged over the fifteen years and grouped into quintiles.

If predictability of future stock returns is due to marketwide factors not yet reflected in stock prices, then the predictive ability of aggregate insider trading should increase with market risk. Table IV is consistent with this prediction. The explanatory power of both *ANT* and *ANS* generally increases with the market risk of the firms.

While not shown, various tests have been conducted to measure the sensitivity of the findings to the empirical methodology. The results shown in this study are not sensitive to the exact definition of either aggregate insider trading or future returns. Using only insider trading data in 9,103 firms with return data instead of all 19,571 firms produces almost identical results. When standardized aggregate net number of transactions, *SANT*, or standardized aggregate net number of shares traded, *SANS*, is

TABLE IV
TIME SERIES REGRESSION OF FUTURE EXCESS STOCK RETURN ON PAST TWELVE-MONTH AGGREGATE INSIDER TRADING ACTIVITY BY MARKET RISK QUINTILES[a]

Panel A: $\sum_{k=t}^{t+m-1} (R_k^i - R_k^f) = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} ANT_k^j$

	$n = 12$, $m = 1$		$n = 12$, $m = 3$		$n = 12$, $m = 6$		$n = 12$, $m = 12$	
(i,j)	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$
1,1	1.42	0.026	3.56	0.041	7.19	0.070	8.79	0.088
	(2.11)		(1.82)		(1.74)		(1.50)	
2,2	0.43	0.003	1.34	0.005	3.39	0.039	6.01	0.227
	(1.15)		(1.13)		(1.63)		(2.19)	
3,3	0.46	0.007	1.47	0.019	3.64	0.077	6.61	0.362
	(1.35)		(1.43)		(1.80)		(2.89)	
4,4	0.55	0.016	1.66	0.040	3.86	0.123	8.23	0.646
	(1.78)		(1.81)		(2.19)		(4.97)	
5,5	0.99	0.025	3.04	0.069	6.56	0.164	13.54	0.603
	(2.16)		(2.26)		(2.51)		(4.55)	
N	168		56		28		14	

Panel B: $\sum_{k=t}^{t+m-1} (R_k^i - R_k^f) = \alpha_0 + \alpha_1 \sum_{k=t-n}^{t-1} ANS_k^j$

	$n = 12$, $m = 1$		$n = 12$, $m = 3$		$n = 12$, $m = 6$		$n = 12$, $m = 12$	
(i,j)	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$	α_1	$\overline{R}^2$
1,1	0.26	0.004	0.77	−0.004	1.68	−0.007	4.84	0.161
	(1.14)		(0.89)		(0.91)		(1.87)	
2,2	0.03	−0.004	0.10	−0.014	0.25	−0.025	0.23	−0.075
	(0.45)		(0.48)		(0.59)		(0.31)	
3,3	0.07	−0.004	0.24	−0.012	0.21	−0.036	0.47	−0.066
	(0.54)		(0.57)		(0.24)		(0.45)	
4,4	0.10	−0.002	0.32	−0.010	1.06	0.007	3.35	0.342
	(0.72)		(0.69)		(1.09)		(2.79)	
5,5	0.65	0.032	1.89	0.077	3.94	0.161	7.26	0.551
	(2.39)		(2.36)		(2.49)		(4.12)	
N	168		56		28		14	

a. See note to Table II.

used, the results are qualitatively similar yet somewhat weaker. Apparently, standardization smooths out some of the informative variation in *ANT* and *ANS*. Moreover, each measure of aggregate insider trading is fitted with a univariate time series model to measure the expected and unexpected components. These tests do not result in additional insights. Both the expected and unexpected components of aggregate insider trading display significant forecasting ability. Also using either the actual returns or the real returns (actual return minus the continuously compounded growth rate of the monthly Consumer Price Index) as the dependent variable yields similar results.

Sensitivity of the results to regression methodology is also examined. The significance levels of the estimated regression coefficients are also assessed using a bootstrapping procedure with 250 replications [Efron, 1982; Freedman and Peters, 1984]. Since the regression residuals usually exhibit significant serial correlation and heteroskedasticity, the significance levels of estimated coefficients are also computed using the Newey and West [1987] covariance matrix if there is serial correlation, or the White [1980] covariance matrix if the serial correlation is not significant. Two lead and lag terms of the residuals are used to compute the Newey-West covariance matrix. In addition, the seemingly unrelated regression (SUR) approach is used. The bootstrapping standard errors for the regression coefficients are generally comparable to the reported OLS standard errors. Although the SUR approach results in somewhat smaller significance levels, the overall inferences remain the same. Both the White and the Newey-West asymptotic t-statistics for the regression coefficients are also substantially greater.

The evidence in Tables II to IV suggests that aggregate insider trading has significant forecasting ability for future excess returns to portfolios of firms. The degree of forecastability of future excess stock returns from 1975 to 1989 (up to 60 percent) exceeds previously reported predictable components of stock returns for short horizons [Fama and French, 1988a, 1988b]. As in previous studies, the forecastability of future excess returns increases with the use of data with longer time horizons (up to twelve months), as well as with an increasing forecast horizon (also up twelve months). Both of these findings agree with the conclusions of previous studies, even though forecasting variables differ [Fama and French, 1988a, 1988b].

B. Insider Trading, Future Real Activity, and Expected Stock Returns

The tests presented next examine the relation between current insider trading, changes in future real activity, and expected stock

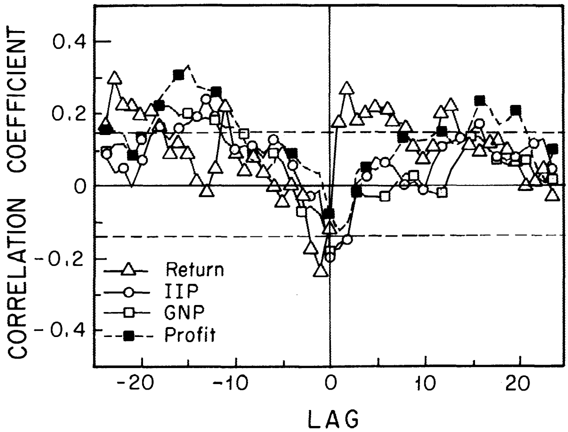

FIGURE II
Cross-Correlations of Aggregate Net Number of Transactions, $ANT_{t\text{-}LAG}$ with Equally-Weighted Average of Stock Returns, RETURN_t, and Growth Rates of Index of Industrial Production, IIP_t, Gross National Product, GNP_t, and After-Tax Corporate Profits, PROFIT_t

returns. Figures II and III show plots of the correlations of ANT^1 with 24 lead and lags of stock returns, term spread, default spread, dividend yields, and growth rates of Gross National Product, Index of Industrial Production, and after-tax corporate profits. The 95

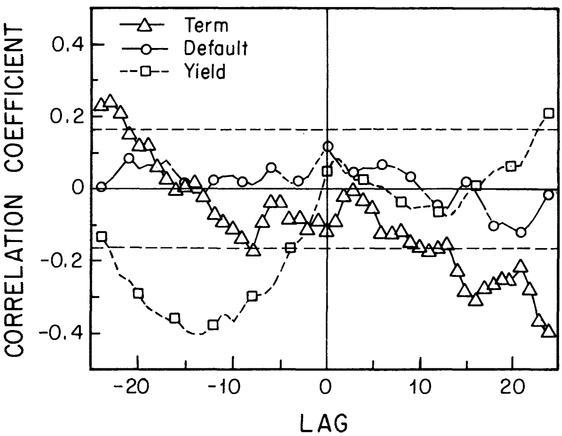

FIGURE III
Cross-Correlations of Aggregate Net Number of Transactions, $ANT_{t\text{-}LAG}$ with Term Spread, TERM_t, Default Spread, DEFAULT_t, and Dividend Yield, YIELD_t

percent confidence bands are indicated with horizontal dashed lines.

Figure II shows that aggregate insider trading is positively correlated with future stock returns up to twenty months in the future. These positive correlations underlie the relations in Tables II to IV. In contrast, aggregate insider trading is negatively correlated with contemporaneous and immediate past returns. Apparently, insiders act as if they were contrarians with respect to past movements in stock prices. Over a three-month period, insiders tend to sell stock following increases in stock prices and buy stock following decreases in stock prices.

Figure II also shows the correlations of aggregate insider trading with growth rates of Gross National Product, Index of Industrial Production, and after-tax corporate profits. Overall, the data in Figure II are consistent with the cash flow hypothesis: aggregate insider trading is positively correlated with all three measures of real activity between twelve to twenty months in the future. Hence, it is plausible that the predictive ability of aggregate insider trading observed in Tables II to IV is due to the ability of insiders to anticipate future cash flows in their own firms. Moreover, aggregate insider trading follows increases in future real activity with a six- to twenty-month lag. However, the correlations do decline with increasing firm size quintiles (not shown).

Figure III shows the correlations of aggregate insider trading with dividend yields, term spread, and default spread, which have been shown to predict changes in future real activity. In Figure III none of the lag zero correlations of aggregate insider trading is significant. Moreover, the correlations remain insignificant for much of the lag structure around lag zero. Hence, Figure III does not support the hypothesis that movements in aggregate insider trading are mostly influenced by changing expectations about future real activity. Otherwise, as expectations about future real activity change, aggregate insider trading patterns would change contemporaneously with movements in dividend yields, and term and default spreads.

The tests presented in Table V further examine the two hypotheses for the explanatory power of aggregate insider trading. In addition to the twelve-month past aggregate insider trading in all firms, Table V includes twelve-month past excess stock returns, dividend yields, term and default spreads, and future growth rates of Gross National Product and after-tax corporate profits as additional predictors of six-month-ahead excess stock returns.

TABLE V

Time Series Regression of Six-Month-Ahead Excess Stock Returns for a Portfolio of 9,103 Firms Against Past Twelve-Month Aggregate Net Number of Insider Transactions (ANT), Twelve-Month Past Excess Stock Returns, Dividend Yield, Term Spread, Default Spread and Growth Rates of Future Gross National Product (GNP) and After-Tax Corporate Profits[a]

$$\sum_{k=t}^{t+5}(R_k^A - R_k^f) = \alpha_0 + \alpha_1\left(\sum_{k=t-12}^{t-1} ANT_k^A\right) + \alpha_2 \sum_{k=t-12}^{t-1}(R_k^A - R_k^f) + \alpha_3\,\text{YIELD}_{t-1} + \alpha_4\,\text{TERM}_{t-1} + \alpha_5\,\text{DEFAULT}_{t-1} + \alpha_6\, g_{t+6,t+8}^{\text{GNP}} + \alpha_7\, g_{t+9,t+11}^{\text{GNP}} + \alpha_8\, g_{t+6,t+8}^{\text{Profit}} + \alpha_9\, g_{t+9,t+11}^{\text{Profit}} + \epsilon_t$$

No.	Constant	$\sum_{k=t-12}^{t-1} ANT_k^A$	$\sum_{k=t-12}^{t-1} (R_k^A - R_k^f)$	$YIELD_{t-1}$	$TERM_{t-1}$	$DEFAULT_{t-1}$	$g_{t+6,t+8}^{\text{GNP}}$	$g_{t+9,t+11}^{\text{GNP}}$	$g_{t+6,t+8}^{\text{Profit}}$	$g_{t+9,t+11}^{\text{Profit}}$	$\bar{R}^2$
(1)	0.990	0.87	−0.004	—	—	—	—	—	—	—	0.134
	(2.64)	(2.39)	(−0.03)								
(2)	−0.404	—	—	10.59	—	—	—	—	—	—	0.112
	(−1.75)			(2.07)							
(3)	−0.209	0.67	—	6.28	—	—	—	—	—	—	0.178
	(−0.89)	(1.74)		(1.13)							
(4)	0.036	1.00	—	—	1.41	—	—	—	—	—	0.191
	(0.67)	(2.73)			(0.94)						
(5)	0.087	0.93	—	—	—	−0.40	—	—	—	—	0.159
	(1.31)	(2.55)				(−0.94)					
(6)	−0.238	0.68	0.042	6.74	—	—	—	—	—	—	0.146
	(−0.88)	(1.72)	(0.29)	(1.15)							
(7)	0.026	1.00	—	—	1.48	0.48	—	—	—	—	0.153
	(0.28)	(2.67)			(0.92)	(0.14)					
(8)	−0.699	0.75	0.202	12.68	3.43	3.93	—	—	—	—	0.178
	(−1.54)	(1.79)	(1.04)	(1.62)	(1.64)	(1.00)					
(9)	0.019	0.95	—	—	—	—	0.55	1.14	—	—	0.185
	(0.43)	(2.72)					(0.83)	(1.27)	—	—	
(10)	0.059	0.77	—	—	—	—	—	—	−0.03	0.68	0.256
	(2.05)	(2.30)							(−0.06)	(2.14)	
(11)	−0.680	0.69	0.136	12.62	1.45	3.55	0.97	1.09	−0.51	0.28	0.097
	(−1.32)	(1.53)	(0.63)	(1.43)	(0.55)	(0.79)	(0.86)	(0.75)	(−0.75)	(0.53)	

a. The regression is estimated over the 28 nonoverlapping six-month periods from January 1976 to December 1989. The term R_k^A denotes the continuously compounded rate of return for the portfolio of 9,103 firms in month k. The term R_k^F denotes the continuously compounded rate of return on one-month Treasury Bills in month k. The coefficient estimates for ANT^A are multiplied by 10^5. The t-statistics are in parentheses.

Once again, the dependent variable is computed over nonoverlapping six-month periods.

Model (1) in Table V presents a regression with aggregate insider trading in all firms and past stock returns as explanatory variables. Model (1) indicates that past stock returns have no marginal explanatory power, while aggregate insider trading has a coefficient estimate of 0.87, with a t-statistic of 2.39 and an adjusted R^2 of 13.4 percent. In comparison, the corresponding simple regression in Table III, Panel A, shows all aggregate insider trading with a coefficient estimate of 0.87, t-statistic of 2.49, and adjusted R^2 of 16.1 percent. Hence, including past stock returns as an additional explanatory variable does not affect either the magnitude or the significance of the coefficient estimate of aggregate insider trading.

In Model (2) a simple regression of dividend yield predicts the six-month-ahead excess stock returns. When included with the aggregate insider trading in Model (3), however, both the point estimate and the t-statistic for the dividend yield are cut in half. In a multiple regression the dividend yield does not have any marginal explanatory power, while the predictive ability of aggregate insider trading is maintained. Moreover, the adjusted R^2 equals 17.8 percent, which is only slightly greater than the 16.1 percent from a simple regression with aggregate insider trading.

Models (4) to (7) in Table V include past stock returns, dividend yields, and term and default spreads in various combinations with aggregate insider trading as explanatory variables. These predictors of time variation in stock returns neither attenuate the predictive ability of aggregate insider trading nor attain marginal explanatory power in multiple regressions. Hence, the predictive ability of aggregate insider trading cannot be fully attributed to one of these variables. Finally, Model (8) includes all variables available at time $t - 1$. Even when all predictive variables are included, aggregate insider trading maintains its marginal explanatory power. The adjusted R^2 of the regression reaches only 17.8 percent which is only slightly higher than the 16.1 percent from a simple regression with *ANT*. Both the dividend yield and term spread also attain marginal explanatory power.

Models (9) and (10) include the future growth rates of Gross National Product and after-tax corporate profits in addition to aggregate insider trading. Future after-tax profits are positively related to the excess stock returns. However, in both Models (9) and (10) the predictive ability of aggregate insider trading is maintained even after taking into account the positive relation between stock returns and future real activity. Hence, a potential errors-in-variables problem from the use of *realized* future real activity rather than *expected* future real activity does not affect the coefficient estimates of aggregate insider trading.

Finally, Model (11) includes all variables in the regressions. In Model (11) all variables show reduced significance levels which suggests increased multicollinearity. The adjusted R^2 declines to 9.7 percent. Nevertheless, the aggregate insider trading variable remains the most significant explanatory variable. Overall, the evidence in Table V suggests that not all of the predictive ability of aggregate insider trading can be attributed to the positive relation between aggregate insider trading and future real activity shown in Figure II.

C. Cross-Sectional Tests

To ensure that the predictive ability of aggregate insider trading is not spurious, cross-sectional tests control for other determinants of future expected stock returns such as market risk, firm size, and past stock returns. All firms with data for market risk, firm size, and stock returns are included in the cross-sectional tests. No insider trading in a given month is again considered a valid observation. Hence, the cross-sectional tests do not condition on insider trading.

The methodology follows that of Fama and MacBeth [1973]. First, two measures of market risk (beta) are computed using even and odd months over a six-year period preceding each month from 1975 to 1989. Second, betas from even months are used in ranking securities while betas from odd months are used in regressions to avoid a regression bias. Firm size is measured as of the end of the previous year. To reduce the measurement errors, securities are grouped into 125 groups based on quintile ranks of aggregate insider trading (*ANT* or *ANS*), beta, and firm size.

Future six-month excess stock returns are regressed against past six-month excess stock returns, past twelve-month *ANT* and *ANS*, log of firm size, and past beta. The regression is then repeated for the remaining 27 nonoverlapping six-month periods from 1976 to 1989. The estimated cross-sectional regression coefficients are then averaged. Standard errors and t-statistics of the estimated regression coefficients are computed using the 28 coefficient estimates from nonoverlapping six-month periods. This methodology ensures that the time series regression coefficients are not constrained.

In Panel A of Table VI the dependent variable is future six-month excess stock returns. The coefficient estimates of both *ANT* and *ANS* are positive and statistically significant. The t-statistics for the aggregate insider trading variables range from 2.76 to 7.67. In contrast, the estimated coefficients for past six-month stock returns, log of firm size, and beta either are only marginally significant, or in the case of past stock returns, are positive rather than negative. Moreover, these additional variables do not attenuate the explanatory power of aggregate insider trading. These results suggest that the predictive ability of aggregate insider trading is not proxy for factors such as market risk, firm size, or past stock returns.

In Panel B of Table VI the dependent variable is again future six-month excess stock returns. However, the twelve-month past insider trading is now computed with a three-month delay to allow for publication lags. Panel B of Table VI shows that the aggregate insider trading predicts future stock returns even after a three-month delay. The other independent variables remain marginally significant. These results further suggest that publicly available data on aggregate insider trading can be used to predict cross-sectional stock returns.

While not shown, the cross-sectional regressions are repeated using future one-month, three-month, and twelve-month stock returns. The results remain uniformly similar. Aggregate insider trading (including no transactions) is a significant cross-sectional predictor of stock returns. In contrast, the cross-sectional predictive ability of past stock returns, firm size, and market risk is only marginally significant.

D. A Simple Predictive Test

While the regression analysis in Tables II to VI shows the strength of the predictive ability of aggregate insider trading, it does not address the following issues. (i) Can outsiders construct a simple trading rule based only on recent insider trading patterns to predict future stock returns? (ii) Can aggregate insider trading patterns be used to predict when future stock returns are negative? (iii) What happens to the predictive ability of the aggregate insider trading patterns when implementation of the trading rule is delayed to ensure that insider trading information becomes publicly available? If the predictability of future stock returns arises

TABLE VI

A Weighted Cross-Sectional Regression of Six-Month-Ahead Excess Stock Returns Against Twelve-Month Past Insider Trading, Past Excess Stock Returns, Log of Firm Size, LV, and Market Risk, β[a]

$$\sum_{k=t}^{t+5}(R_k^i - R_k^f) = \alpha_0 + \alpha_1\left(\sum_{k=t-12-d}^{t-1-d} ANT_k^i\right) + \alpha_2\left(\sum_{k=t-12-d}^{t-1-d} ANS_k^i\right) + \alpha_3 \sum_{k=t-12}^{t-1}(R_k^i - R_k^f) + \alpha_4 LV + \alpha_5\beta + \epsilon_t$$

Model No.	Panel A: $d = 0$ Constant	ΣANT	ΣANS	$\Sigma R^i - R^f$	LV	β	Panel B: $d = 3$ Constant	ΣANT	ΣANS	$\Sigma R^i - R^f$	LV	β
(1)	−0.033	181.4	—	0.068	0.005	0.041	−0.036	136.3	—	0.154	0.005	0.039
	(−0.60)	(7.67)	—	(1.48)	(1.00)	(1.78)	(−0.81)	(7.10)	—	(4.27)	(1.12)	(1.38)
(2)	−0.012	—	141.0	0.085	0.003	0.038	−0.021	—	122.5	0.181	0.003	0.036
	(−0.21)	—	(3.44)	(1.81)	(0.67)	(1.65)	(−0.43)	—	(3.88)	(4.89)	(0.87)	(1.29)
(3)	0.069	117.3	—	—	—	—	0.059	86.1	—	—	—	—
	(2.16)	(3.14)	—	—	—	—	(1.90)	(2.04)	—	—	—	—
(4)	0.069	—	114.1	—	—	—	0.059	—	82.1	—	—	—
	(2.15)	—	(2.76)	—	—	—	(1.91)	—	(1.96)	—	—	—
(5)	0.063	—	—	0.015	—	—	0.061	—	—	0.185	—	—
	(2.62)	—	—	(0.17)	—	—	(2.03)	—	—	(1.64)	—	—
(6)	0.020	—	—	—	0.004	—	−0.014	—	—	—	0.006	—
	(0.26)	—	—	—	(0.85)	—	(−0.22)	—	—	—	(1.59)	—
(7)	0.025	—	—	—	—	0.037	0.023	—	—	—	—	0.039
	(1.72)	—	—	—	—	(1.61)	(2.09)	—	—	—	—	(1.13)

a. The terms $R_k^i, \ldots, 125$, denote the continuously compounded returns in month k for the portfolio i. R_k^f denotes the continuously compounded return on one-month Treasury Bill in month k. ANT_k^i, $i = 1, 125$, denotes the net number of transactions by insiders in month k for portfolio i. ANS_k^i, $i = 1, 125$, denotes the net number of shares traded by insiders in month k for portfolio i. LV is the log of the market value of equity for the previous year (in \$000), while β denotes the market risk. A cross-sectional regression is run over 125 grouped observations over nonoverlapping six-month periods, based on quintiles of market risk, firm size, and insider trading activity. The regression coefficients shown are the average for the 28 nonoverlapping six-month periods (27 in Panel B). The t-statistics for the average coefficients are shown in parentheses. The weights in the regressions are the number of firms in each group. The regression coefficients are multiplied by 10^5 for ANT and 10^9 for ANS.

solely from movements in the expected future state of the economy, then it is reasonable to assume that predicted risk premiums will be positive. In contrast, if the predictability of stock returns in part reflects movements away from fundamentals, then predicted risk premiums can be either positive or negative.

To construct a simple decision rule, the past twelve-month aggregate net number of transactions in the smallest quintile of firms, ANT_t^1 is used to forecast future stock returns. When the past twelve-month ANT_t^1 is positive, a BUY dummy is set to one. Otherwise, it is equal to zero. On average, insiders in small firms tend to purchase stock more frequently than they sell stock, hence—ANT_t^1 is positive (see Table I). Therefore, when ANT_t^1 is negative, aggregate insider trading provides an unusually negative signal. These tests are also repeated using the aggregate net number of transactions in all firms ANT_t^{ALL}, with similar results.

Table VII presents average returns to the strategy described above. The dependent variables are the nonoverlapping, excess returns to size quintiles, each containing about 1,820 firms. The independent variable is the BUY_{t-1} dummy. In Panel A of Table VII the holding periods are one month, three months, and six months immediately following the month when the aggregate insider trading activity is measured. Hence, in Panel A insider trading information is assumed to be obtained without delay. In Panel A the regressions contain 168, 56, and 28 observations for the one-month, three-month, and six-month holding periods, respectively. The dummy variable is zero in 24, 6, and 3 subperiods, respectively.

The intercept term in Models (1) through (5) in Table VII measures the excess returns to size quintiles when the BUY dummy is zero; hence, the aggregate net number of transactions gives a negative signal. In model (1) of Panel A, given a negative signal, the average excess return to the smallest quintile portfolio is -1.84 percent per month, with a t-statistic of -1.57, which borders on marginal significance.[5] In models (2) through (5) excess returns are either zero or negative, although statistically insignificant. The BUY dummy is positive in all quintiles and statistically significant in the first three quintiles.

Panel A of Table VII also shows the excess returns for three-month and six-month holding periods. In the first quintile the intercept term is negative and marginally significant with

5. If market participants use a larger information set, they may still expect future stock returns to be positive.

TABLE VII

TIME SERIES REGRESSION OF FUTURE EXCESS STOCK RETURN ON AN INDICATOR VARIABLE BASED ON PAST TWELVE-MONTH AGGREGATE INSIDER TRADING ACTIVITY BY QUINTILES OF FIRM SIZE[a]

$$\sum_{k=t}^{t+m-1} (R_k^i - R_k^f) = \alpha_0 + \alpha_1 BUY_{t-1} \quad \text{and} \quad BUY_{t-1} \begin{cases} = 1 \text{ if } \sum_{k=t-12-d}^{t-1-d} ANT_k^1 > 0 \\ = 0, \text{ otherwise} \end{cases}$$

Panel A: $d = 0$; No delay in implementation

	$m = 1$ [$N = 168$]			$m = 3$ [$N = 56$]			$m = 6$ [$N = 28$]		
i	α_0	α_1	$\bar{R}^2$	α_0	α_1	$\bar{R}^2$	α_0	α_1	$\bar{R}^2$
(1)	−0.0184	0.0276	0.022	−0.0848	0.1129	0.057	−0.1812	0.2388	0.106
	(−1.57)	(2.18)		(−1.66)	(2.09)		(−1.64)	(2.05)	
(2)	−0.0136	0.0276	0.019	−0.0695	0.1117	0.053	−0.1578	0.2445	0.118
	(−1.10)	(2.07)		(−1.34)	(2.03)		(−1.47)	(2.15)	
(3)	−0.0080	0.0237	0.014	−0.0434	0.0900	0.036	−0.1000	0.1947	0.089
	(−0.66)	(1.81)		(−0.89)	(1.75)		(−1.04)	(1.90)	
(4)	−0.0036	0.0200	0.009	−0.0252	0.0737	0.026	−0.0603	0.1578	0.072
	(−0.30)	(1.57)		(−0.57)	(1.58)		(−0.71)	(1.76)	
(5)	0.0000	0.0138	0.003	−0.0067	0.0488	0.010	−0.0202	0.1051	0.036
	(0.00)	(1.24)		(−0.18)	(1.25)		(−0.29)	(1.42)	

Panel B: $d = 3$; Three-month delay in implementation

	$m = 1$ [$N = 165$]			$m = 3$ [$N = 55$]			$m = 6$ [$N = 27$]		
i	α_0	α_1	$\bar{R}^2$	α_0	α_1	$\bar{R}^2$	α_0	α_1	$\bar{R}^2$
(1)	−0.0198	0.0267	0.024	−0.044	0.0600	0.006	−0.0492	0.0770	−0.023
	(−1.79)	(2.23)		(−0.91)	(1.16)		(−0.43)	(0.64)	
(2)	−0.012	0.0230	0.013	−0.0211	0.0508	−0.002	−0.0161	0.0749	−0.024
	(−0.97)	(1.78)		(−0.42)	(0.95)		(−0.14)	(0.62)	
(3)	−0.003	0.0164	0.004	0.0008	0.0346	−0.010	0.0078	0.0641	−0.025
	(−0.30)	(1.29)		(0.02)	(0.69)		(0.08)	(0.00)	
(4)	0.002	0.0116	−0.001	0.0115	0.0273	−0.012	0.0351	0.0431	−0.031
	(0.18)	(0.93)		(0.027)	(0.60)		(0.40)	(0.46)	
(5)	0.008	0.004	−0.006	0.0280	0.0062	−0.018	0.0651	0.0027	−0.040
	(0.80)	(0.32)		(0.77)	(0.16)		(0.91)	(0.04)	

a. The sample period is 180 months from January, 1975 to December 1989. The terms R_k^i, $i = 1, \ldots, 5$ denotes the continuously compounded returns in month t for the firm size quintiles. R_k^f denotes the continuously compounded return on one-month Treasury Bills in month k. ANT^1 denotes the aggregate net number of transactions by insiders for the smallest size quintile. The t-statistics are in parentheses. The adjusted R^2's are from ordinary least squares regressions. N denotes the number of observations in the regressions.

t-statistics equal to −1.66 and −1.64, respectively. For larger firms the intercept terms are also negative, although statistically insignificant. The coefficient estimate of the *BUY* dummy is positive in all cases and statistically significant in a majority of cases.

The point estimates of intercept and slope coefficients indicate large stock returns. For instance, for the six-month holding period, when the *BUY* dummy is zero, average excess six-month stock returns to the smallest quintile of firms equals −18.12 percent. When the *BUY* dummy equals one, the average excess six-month stock returns increases by 23.88 percent, to 5.76 percent (23.88 percent minus 18.12 percent).

The analysis in Panel A of Table VII suggests that a simple trading rule based only on the recent insider trading activity predicts future excess stock returns. Moreover, aggregate insider trading activity in the smallest quintile of firms also predicts the excess stock returns in larger firms as well. This finding corroborates the interpretation that the predictive ability of aggregate insider trading is due to economywide factors common to all firms.

When insider trading gives negative signals, the excess returns to a portfolio of a large number of firms is negative. Hence, aggregate insider trading can also predict times when stock prices are too high. Finally, the magnitude of the predicted returns is large and likely to be economically significant.

Panel B of Table VII implements the decision rule based on aggregate insider trading activity with a three-month delay to allow for the public dissemination of insider trading information. The results in Seyhun [1986] show that 95 percent of insider trading activity is reported to the SEC within a three-month period. Hence, anyone can obtain insider trading information after it is reported to the SEC. The tests in Table VII are also replicated for a six-month delay, yielding similar results.

Given a three-month implementation delay and one-month holding period in Panel B of Table VII, the excess return to the smallest quintile of firms when the *BUY* dummy is zero, equals −1.98 percent with a t-statistic of −1.79. This value is significant at the 10 percent level. The coefficient of *BUY* dummy equals 2.67 percent with a t-statistic of 2.23. Hence, even after allowing for a three-month delay in implementation, recent aggregate insider trading patterns predict future excess stock returns. For larger firm size quintiles the predictive ability of aggregate insider trading falls sharply. Furthermore, for three-month and six-month holding periods combined with a three-month delay, aggregate insider trading does not produce statistically significant predictive ability for any size quintile. These results suggest that the predictive ability of aggregate insider trading remains minimal when delays in implementation of the trading rules are taken into account.

The predicted negative expected returns to various portfolios shown in Table VII make it difficult to attribute all predictive ability of aggregate insider trading to changes in business conditions. An unexpected improvement in current business conditions should result in lower positive expected future returns, not negative expected future returns. A negative expected future return, however, is consistent with the fads hypothesis.

V. Conclusions

The evidence presented in this study documents a strong relation between past aggregate insider trading and future excess stock returns. During the period 1975 to 1989, up to 60 percent of the variation in twelve-month-ahead excess stock returns can be forecast using the previous twelve-month aggregate insider trading. This finding substantially exceeds the previously documented degree of predictability of short horizon stock returns using past stock returns to dividend yields. Aggregate insider trading in small firms predicts the future stock returns to larger (nonoverlapping) groups of firms. The predictability of stock returns increases with the length of forecasting horizon, the number of months of past insider trading, and market sensitivity of stocks.

Evidence also indicates that current aggregate insider trading is positively related to future real activity as measured by the growth rates of after-tax corporate profits, the Index of Industrial Production, and the Gross National Product. The ability of aggregate insider trading to forecast future stock returns, however, cannot be completely attributed to the relation between insider trading and future real activity. Insider trading retains marginal explanatory power when future real activity is included as an additional explanatory variable. Moreover, other predictors of time series variation in stock returns such as past stock returns, dividend yields, and term and default spreads do not attenuate the predictive power of aggregate insider trading. This evidence suggests that aggregate insider trading captures a component of stock returns not related to movements in future real activity, dividend yields, past stock returns, and term or default spreads.

The cross-sectional tests corroborate the time series tests. Aggregate insider trading predicts cross-sectional future stock returns. Moreover, the predictive ability of aggregate insider trading is not attenuated when predictors of cross-sectional stock returns such as past stock returns, market risk, and firm size are included as additional explanatory variables.

A simple, predictive test indicates that aggregate insider trading signals can be used to predict the future excess stock returns to be negative. Moreover, the magnitude of the forecast future excess returns is likely to be economically meaningful. For instance, given a sell signal based on twelve-month past aggregate insider trading, predicted excess returns to zero-beta portfolios range from −1.8 percent to −18.1 percent for one- to six-month holding periods, respectively.

The overall evidence suggests that it is difficult to attribute all of the predictable movements in stock returns to movements in equilibrium expected returns. Instead, the evidence suggests that both changes in business conditions as well as movements away from fundamentals contribute to the information content of aggregate insider trading.

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