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The Conditional Performance of Insider Trades

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ABSTRACT

This paper estimates the performance of insider trades on the closely held Oslo Stock Exchange (OSE) during a period of lax enforcement of insider trading regulations. Our data permit construction of a portfolio that tracks all movements of insiders in and out of the OSE firms. Using three alternative performance estimators in a time-varying expected return setting, we document zero or negative abnormal performance by insiders. The results are robust to a variety of trade characteristics. Applying the performance measures to mutual funds on the OSE, we also document some evidence that the average mutual fund outperforms the insider portfolio.

CORPORATE INSIDERS, I.E., INDIVIDUALS closely related to the firm either through direct employment or through participation on supervisory committees and boards, will from time to time possess information about the firm's future cash flow which is not yet reflected in the firm's stock price. Insiders who trade on the basis of such information tend to purchase stocks just prior to abnormal price increases and to sell just prior to abnormal price declines. Employing traditional event-study techniques, in which equal-weighted average abnormal stock returns are estimated over a fixed time period following insider trades, the extant empirical literature tends to support this "buy low and sell high" hypothesis. For example, Jaffe (1974) and Seyhun (1986) present evidence of significant abnormal stock returns following reported insider trades on the New York and the American Stock Exchanges. Similarly, Baesel and Stein (1979) and Fowler and Rorke (1984) conclude that insiders on the Toronto Stock Exchange earn abnormal profits, and Pope, Morris, and Peel (1990) reach a similar conclusion for firms in the United Kingdom.

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This paper develops a new empirical methodology that mimics the true performance of insider trades more accurately than the traditional event-study approach. This methodology, when applied to a stock market with a reputation for being an "insider's market," produces evidence of zero or negative abnormal insider returns. Moreover, it appears that portfolios formed from all insider holdings are outperformed by portfolios of managed mutual funds on the same stock exchange. We reach these conclusions using the population of more than 18,000 reported insider trades on the Oslo Stock Exchange (OSE) from January 1985 through December 1992. Over this period, the OSE experienced a significant surge in investments by the general public as well as by foreign investors. Nevertheless, the ownership structure of OSE stocks continues to be concentrated, with insiders accounting for more than 14 percent of the market.[1] This ownership structure, combined with a relatively volatile stock market and lax enforcement of insider trading laws during our sample period, makes the OSE a particularly interesting laboratory for studying the potential profits from insider trades.[2]

Our performance analysis is novel in that it tracks all changes in the level of insiders' individual stock holdings and incorporates and extends performance measures recently developed in the literature on mutual funds. We draw inferences using various portfolios of insider holdings, as well as three different conditional performance measures, each allowing expected stock returns to be time-varying. Allowing for time-variation in expected stock returns is important in light of the growing evidence that publicly available information such as bond yields and past stock price movements to some extent predict future returns. For example, if current yield spreads indicate that a certain stock will have a relatively high expected return over the next period, an insider who conditions on this information when trading will exhibit superior performance relative to a benchmark portfolio that assumes (unconditional) constant expected returns. Because this insider has not exploited any private information, such "performance" is not considered superior in our context and therefore is eliminated.

[1] In 1992, the total market capitalization of OSE stocks was approximately $35 billion aggregated over 120 listed firms. Within the average OSE firm, the 10 largest shareholders owned 67 percent of the total equity. Moreover, 80 percent of the firms had at least one shareholder (excluding the government) holding 20 percent or more of the equity. The proportion of OSE equity owned by foreign investors increased steadily from 15 percent in 1986 to 30 percent in 1992 (source: OSE annual reports).

[2] First-generation insider trading regulations were introduced in 1985, at the beginning of our sample period. From 1985 through 1992 there were no convictions under the insider trading statutes. Stricter, second-generation regulations were introduced after 1992. Heinkel and Kraus (1987) also present an interesting laboratory: they study reported insider trades in a sample of all new junior resource stock listings on the Vancouver Stock Exchange (VSE) between June 1979 and March 1981 (a total of 132 firms and 1932 transactions). The VSE has a reputation as a large-variance speculative market, where stock promoters and insiders tend to be large shareholders. They find no significant difference in the average returns to insiders and outsiders in these stocks.

In our performance analysis, we first develop and estimate a conditional event-study measure that extends the traditional event-study technique to a conditional, multifactor setting. Second, we apply a conditional version of the so-called "Jensen's alpha," also examined by Ferson and Schadt (1996) in the context of mutual funds. Third, we develop a conditional version of the portfolio-weight performance measure first suggested by Cornell (1979) and applied in particular by Grinblatt and Titman (1993) to measure mutual fund performance.

We find that a standard event study analysis produces evidence of positive abnormal performance following insider sale transactions, not unlike the findings reported by Seyhun (1986). However, this abnormal performance disappears when insiders' actual value-weighted portfolio returns are used or when a multifactor market model allowing for time-varying expected returns is applied. Moreover, neither the conditional Jensen's alpha nor the conditional portfolio-weight performance measures indicate positive abnormal performance by insiders. In fact, there is some evidence of negative insider performance. These conclusions are robust with respect to trade size, size of holdings in the firm, whether the net trade in the firm is a purchase or a sale, or whether we weigh the trades by insiders' percentage holdings or total equity in the firm.

For comparison, we also provide evidence on the conditional performance of seven major mutual funds on the OSE.[3] In contrast to the decentralized (and partly independent) portfolio decisions by individual insiders, the managed fund portfolios have an administrative advantage in that asset allocation decisions can be optimized across the entire fund portfolio. Interestingly, we find little systematic evidence that the mutual funds outperform the OSE market but there is some evidence that the conditional performance of the average mutual fund exceeds that of the aggregate insider portfolio. Although this result is not pursued further in this paper, one possible explanation is that insiders enjoying corporate control benefits from their ownership positions decide against selling shares even when publicly available (conditioning) information suggests that such sales may increase average returns.

The rest of the paper is organized as follows. Section I characterizes our main empirical approaches to performance measurement. Section II describes our data on insider trades and mutual funds. Section III presents our estimates of insider performance, and the performance of mutual funds is discussed in Section IV. Section V concludes the paper.

I. Conditional Performance Evaluation: Methodology

Let $r_{i,t+1}$ denote the excess return on asset i in period $t+1$ (in excess of the risk-free rate $r_{f,t+1}$) and let $E(r_{i,t+1}|Z_t^*)$ be the expected return conditional on a set of public information available at time t, Z_t^*. Suppose uninformed

[3] Ferson and Schadt (1996), Christopherson, Ferson, and Glassman (1996), and Chen and Knez (1996) also estimate mutual fund performance within a conditional framework.

investors trade based on Z_t^*, generating time-varying expected returns of $E(r_{i,t+1}|Z_t^*)$, and that these investors' trades are otherwise independent of the assets' subsequent price changes. Informed investors use additional, private information I_t to correlate trades with subsequent abnormal returns,

$$\epsilon_{i,t+1} \equiv r_{i,t+1} - E(r_{i,t+1}|Z_t^*).$$

As a result of their ability to "buy low and sell high," the conditional expected return to informed investors exceeds the expected return to uninformed investors; that is,

$$E(r_{i,t+1}|Z_t^*, I_t) - E(r_{i,t+1}|Z_t^*) > 0.$$

The purpose of our empirical analysis is to estimate this difference in conditional expected returns for portfolios of insider holdings as well as for managed mutual funds.

In the following, we first discuss our choice of portfolio representations of insider holdings and trades. We next introduce the conditional event-study framework as well as the conditional Jensen's alpha approach. These methods require specification of a model relating the risk and return on a benchmark portfolio, which serves as a proxy for $E(r_{i,t+1}|Z_t^*)$. We then develop our third performance measure, which is the conditional covariance between individual portfolio weights at time t, ω_{it}, and subsequent abnormal return realizations; that is, $\text{Cov}(\omega_{it}, \epsilon_{i,t+1}|Z_t^*)$. An advantage of the third measure, given data on portfolio weights, is that it does not require explicit specification of an expected return model.

A. Portfolio Aggregation

It is common in the event-study literature on insider trading to estimate the equal-weighted average abnormal return over a fixed time period following insider trades. This approach, which is included as a special case here as well, is useful in terms of testing the hypothesis that insiders tend to trade prior to subsequent abnormal movements in stock prices. However, because a cross-sectionally fixed event window does not accurately represent insiders' actual *holding* periods, the event-study performance analysis does not produce estimates of the expected gains from insider trading.

In this paper, we instead aggregate insider stock holdings each month, akin to an insider fund, and track the performance of this fund through time. Of course, individual insiders do not constrain their personal portfolio choices to the set of firms where they are insiders, so this aggregate insider portfolio is not optimal from the perspective of any individual insider. An analogous argument holds for mutual fund portfolios, unless the funds are viewed by all investors as belonging to the set of efficient portfolios. Regardless, the abnormal performance of this portfolio is of particular concern to uninformed investors or mutual fund managers actively trading in broad-based stock portfolios, and whose investment decisions depend on the expected loss from trading against (informed) insiders in the market. Moreover, the abnormal performance of the insider fund is directly comparable to the abnormal performance of managed mutual funds.

We examine two alternative definitions of the insider portfolio weight of security i at time t, *value weights*, ω_{it}^{h}, and *ownership weights*, ω_{it}^{s}, where

$$\omega_{it}^{h} \equiv h_{it} \Big/ \sum_{i=1}^{N_p} h_{it}, \tag{1}$$

$$\omega_{it}^{s} \equiv (s_{it}/S_{it}) \Big/ \sum_{i=1}^{N_p} (s_{it}/S_{it}), \tag{2}$$

and where N_p is the total number of securities in the portfolio, h_{it} is the total market value of all insiders' holdings in firm i at the end of month t, and S_{it} and s_{it} denote the total number of shares outstanding and the number of shares held by insiders in firm i at the end of month t, respectively. By construction, these weights sum to one.

Both the value and ownership weights reflect the level of insider investment in firm i. The former (ω_{it}^{h}) assigns greater weight to firms with relatively large dollar values of insider investment, and the latter (ω_{it}^{s}) gives greater weight to relatively large proportional insider ownership in the firm. Using these weights, we examine the performance of the total insider portfolio as well as subportfolios based on various trade characteristics such as the size and direction of the trade. Because trade-based portfolios zero out periods of nontrading from the return series, one can think of these as producing a marginal performance estimate. This contrasts with the average monthly performance estimate resulting from using both trading and nontrading periods in the estimation.

The difference between the average and marginal performance estimates lies in the impact on portfolio returns of months with zero change in insider holdings. If a decision *not* to trade also reflects inside information, then the average performance estimate has greater power to detect superior performance. This is also the relevant portfolio concept for an analysis of the expected loss to outsiders from trading against insiders, and for comparing the performance of insiders to the performance of managed portfolios such as mutual funds. On the other hand, the possibility of loss of significant corporate control benefits may cause the typical insider not to trade except when inside information is particularly valuable. In this case, the marginal or trade-based performance concept has greater power to register abnormal performance.

The standard event-study performance measure is similar to the marginal performance concepts in that it also conditions on an insider *trade.* However, the event study technique does not track insider trades during the fixed event window following the insider trade date. The typical event study also equally weighs abnormal returns across the securities with insider trades. Relative to our weights, such equal weights give greater weight to firms with smaller insider holdings.

B. Conditional Portfolio Benchmark Return Approach

Assume that expected excess returns follow a K-factor equilibrium model (see, e.g., Connor and Korajczyk (1995)),

$$E(r_{i,t+1}|Z_t^*) = \sum_{j=1}^{K} \beta_{ij}(Z_t^*)\lambda_j(Z_t^*), \tag{3}$$

where $\beta_{ij}(Z_t^*)$ is the systematic risk of the jth factor, and $\lambda_j(Z_t^*)$ is the jth expected factor risk premium, $E(F_{j,t+1}|Z_t^*) - r_{f,t+1}$. In this formulation, the factors F_j are represented by traded securities, and both the systematic risks and expected risk premia are allowed to vary through time as a function of the publicly available information Z_t^*.

Below, in the event-study approach, we estimate an empirical version of equation (3) that adds a firm-specific intercept term as well as event parameters capturing abnormal performance. Under the Jensen's alpha approach, we estimate equation (3) without event parameters and where the intercept term itself measures abnormal performance.

B.1. Conditional Event Study

We estimate abnormal returns over an event window consisting of W months including and following the month of an insider trade (event month 0). Let $\boldsymbol{\mu}_{\mathbf{e_p}}$ denote the $(W \times 1)$ vector of monthly abnormal returns over the event window for portfolio p. The abnormal return vector $\boldsymbol{\mu}_{\mathbf{e_p}}$ is estimated jointly with the parameters in the following multifactor regression model:

$$r_{p,t+1} = a_p + \mathbf{b}_\mathbf{p}'(\mathbf{F_{t+1}} \otimes \mathbf{Z_t}) + \boldsymbol{\mu}_{\mathbf{e_p}}'\mathbf{D_{p,t+1}} + \epsilon_{p,t+1}, \tag{4}$$

where $\mathbf{F_{t+1}}$ and $\mathbf{Z_t}$ are vectors of observable (traded) risk factors and information variables. Furthermore, $\mathbf{b_p}$ is a $(KL \times 1)$ vector of coefficients associated with time-varying risk parameters, and $\mathbf{D_{p,t+1}}$ is a $(W \times 1)$ vector of zeros and ones. When $t + 1$ is outside the event window, $\mathbf{D_{p,t+1}}$ is a vector of zeros. When $t + 1$ is inside the event window, $\mathbf{D_{p,t+1}}$ contains zeros and the value one for the corresponding month in the event window. To illustrate, in Section III we use a total event window extending from the month of the insider trade (month 0) through six months after the trade ($W = 7$). In this case, the month 0 abnormal return is estimated as the first element of $\mu_{\mathrm{e_p}}$ by setting $\mathbf{D_{p,t+1}}$ equal to $(1, 0, 0, 0, 0, 0, 0)'$.[4]

The estimation proceeds in a standard event-study fashion: Let month e_1 be the first calendar month for which we have data on insider trades, and form a fixed-weight portfolio of all firms with nonzero net insider trades in this month. Assuming this portfolio is not empty, let e_1 denote "event month 0 for portfolio 1." The excess return of portfolio e_1 is regressed using equation (4) over a total of T months starting in event month $e_1 - (T - W)$. The regression yields a vector of estimates of the event parameters for months e_1 through $e_1 + W - 1$, denoted $\hat{\boldsymbol{\mu}}_{\mathbf{e_1}}$. Moving forward to the next month with nonzero net insider trades, denoted e_2 ("event month 0 for portfolio 2"), the regression is repeated, yielding a second vector of estimates $\hat{\boldsymbol{\mu}}_{\mathbf{e_2}}$. Moving forward in this manner through the entire sample period yields a total of E vectors of event parameter estimates $\hat{\boldsymbol{\mu}}_{\mathbf{e_p}}$, $p = 1, \ldots, E$; that is, one vector for each of the E portfolios. In Section III, we report the average value of $\hat{\mu}_{\mathrm{e_p}}$ across the E portfolios.

B.2. Conditional Jensen's alpha

Following Ferson and Harvey (1993) and Ferson and Korajczyk (1995), model (3) can be estimated for a portfolio p with an intercept term α_p. A portfolio strategy that depends only on information $\mathbf{Z_t}$ will generate abnormal returns that have mean zero and are uncorrelated with $\mathbf{Z_t}$. Consequently, such a portfolio strategy will yield an estimate of α_p that is equal to zero. The constant term α_p is a conditional version of the classical "Jensen's alpha" developed and applied by Jensen (1968) in the context of the unconditional single-factor capital asset pricing model (CAPM). Active fund management causes the fund's systematic risk to vary through time; therefore, estimation of Jensen's alpha assuming constant systematic risk produces a bias in the estimate of Jensen's alpha (see Grinblatt and Titman (1989) for details). But because equation (3) allows systematic risks to vary with the public information Z_t^*, our conditional model framework mitigates this bias.

[4] Equation (4) generalizes the event study estimation technique found in the literature to a multifactor, time-varying model similar to models in Shanken (1990) and used by Ferson and Schadt (1996). A simplified form of the equation, assuming one factor (the market index) and constant (unconditional) expected returns, yields the traditional market model conditional on event-parameters; that is,

$$r_{p,t+1} = \alpha_p + \beta_p r_{m,t+1} + \boldsymbol{\mu}'_{\mathbf{e_p}} \mathbf{D_{p,t+1}} + \epsilon_{p,t+1}.$$

See, for example, Thompson (1985) for a comparison of this event-parameter approach to estimating abnormal returns to the traditional two-step "residual analysis" approach, and Eckbo (1985) for an early application. The residual analysis method involves first estimating the return-generating process and, in the second step, calculating the prediction errors over the event window.

The performance measure α_p is estimated using the following system of moment conditions:

$$\mathbf{u1_{p,t+1}} = \mathbf{F_{t+1}} - \gamma_{\mathbf{p}}'\mathbf{Z_t} \tag{5}$$

$$\mathbf{u2_{p,t+1}} = (\mathbf{u1_{p,t+1}}\mathbf{u1'_{p,t+1}})(\kappa_{\mathbf{p}}'\mathbf{Z_t}) - \mathbf{u1_{p,t+1}}r_{p,t+1} \tag{6}$$

$$u3_{p,t+1} = r_{p,t+1} - \alpha_p - (\gamma_{\mathbf{p}}'\mathbf{Z_t})'(\kappa_{\mathbf{p}}'\mathbf{Z_t}). \tag{7}$$

If the model is well specified, the following orthogonality conditions must hold:

$$E(\mathbf{u1_{p,t+1}}\mathbf{Z_t'}, \mathbf{u2_{p,t+1}}\mathbf{Z_t'}, u3_{p,t+1}) = 0, \tag{8}$$

which we estimate using Hansen's (1982) generalized method of moments (GMM) estimator.[5]

The system (5) through (7) has an intuitive interpretation: First, equation (5), when multiplied by $\mathbf{Z_t}$, forms L OLS normal equations for each regression of the factors in $\mathbf{F_{t+1}}$ on the information variables $\mathbf{Z_t}$. That is, we assume that the "unrestricted" conditional expected factor returns are linear in

$$\mathbf{Z_t} : E(\mathbf{F_{t+1}}|\mathbf{Z_t}) = \gamma_{\mathbf{p}}'\mathbf{Z_t}.$$

The fitted values, $\hat{\gamma}_{\mathbf{p}}'\mathbf{Z_t}$, are used to model the conditional expected risk premia, and the residuals $\mathbf{\hat{u}1_{p,t+1}}$ are used to estimate conditional variances and covariances. Second, defining the conditional factor betas as

$$\beta_{\mathbf{pt}} \equiv [\mathrm{Var}(\mathbf{F_{t+1}}|\mathbf{Z_t})]^{-1}\mathrm{Cov}(\mathbf{F_{t+1}}, r_{p,t+1}|\mathbf{Z_t}),$$

[5] The estimation procedure is as follows: The system (5) through (7) has a total of $2K + 1$ equations. Since, in equation (8), the first $2K$ equations in system (5) through (7) are multiplied by the L information variables $\mathbf{Z_t}$, the system has a total of $R = 2KL + 1$ sample orthogonality conditions. With time-varying betas, the total number of parameters estimated is $P = 2KL + 1$, so that the system is exactly identified. With constant conditional betas (i.e., imposing $\kappa_{\mathbf{p}}' = (\kappa_{\mathbf{p0}}, \mathbf{0}, \ldots, \mathbf{0})$, where $\kappa_{\mathbf{p0}}$ is a $K \times 1$ vector of coefficients and $\mathbf{0}$ is a $K \times 1$ vector of zeros) the number of parameters estimated is $P = K(L + 1) + 1$. Let $\mathbf{e_t}$ denote a vector of the R orthogonality conditions stacked into one column, and let $\mathbf{g_T} = (1/T)\sum_{t=1}^{T}\mathbf{e_t}$, where T is the total number of periods in the time series. GMM chooses the vector of the P parameters, $\hat{\theta}_{\mathbf{p}}$ containing $\hat{\gamma}_{\mathbf{p}}$, $\hat{\kappa}_{\mathbf{p}}$, and $\hat{\alpha}_{\mathbf{p}}$, to minimize the quadratic form $\mathbf{g_T'W_Tg_T}$, where $\mathbf{W_T}$ is a semipositive definite weighting matrix. Hansen (1982) shows that the $\mathbf{W_T}$ that minimizes the asymptotic covariance matrix of the parameter estimates is the inverse of the estimated variance–covariance matrix of $\mathbf{e_t}$. Given an estimate of $\mathbf{W_T}$, GMM uses the P linear combinations of $(\partial\mathbf{g_T'}/\partial\theta_{\mathbf{p}})\mathbf{W_Tg_T}$ to estimate $\theta_{\mathbf{p}}$. Under the null hypothesis that the model is true and that conditional betas are constant, the $R - P = K(L - 1)$ orthogonality conditions not used in the estimation of the parameters should be close to zero; that is, the more likely these overidentifying restrictions are valid, the better the fit of the model. Hansen (1982) uses this intuition to derive a goodness-of-fit test statistic for the minimized value of the objective function $T\mathbf{g_T'W_Tg_T}$ that is asymptotically χ^2 with $R - P$ degrees of freedom. As pointed out to us by the referee, this goodness-of-fit test statistic is also the test statistic for the hypothesis that the conditional betas are constant, against the alternative that betas vary according to $\kappa_{\mathbf{p}}'\mathbf{Z_t}$ (see Newey and West (1987)).

then equation (6) is the pseudoregression of the estimates $\beta_{\mathbf{pt}}$ on the instruments $\mathbf{Z_t}$, yielding the $L \times K$ matrix of regression coefficient estimates $\hat{\kappa}_{\mathbf{p}}$. The fitted values $\hat{\kappa}'_{\mathbf{p}}\mathbf{Z_t}$ then represent our estimates of the time-varying betas. Third, equation (7) defines the average abnormal performance parameter α_p to be the difference in the realized unconditional excess return on portfolio p and the unconditional mean of the product of the conditional beta estimates and estimates of the conditional risk premia. In sum, α_p measures the average return on portfolio p relative to the return on a time-varying benchmark portfolio.

Ferson and Harvey (1991) and Evans (1994) argue that time-variation in conditional betas for passive portfolios is economically and statistically small in the United States. On the other hand, Ferson and Schadt (1996) find that time-varying betas are important in their measurement of the performance of managed U.S. mutual funds. Because no comparable study exists for the Oslo Stock Exchange, the subsequent empirical analysis reports estimates of α_p assuming both time-varying and constant conditional betas.

C. Conditional Portfolio Weight Measure

As pointed out by Grinblatt and Titman (1989, 1993), absent superior information and assuming expected returns are constant, the average covariances of portfolio weights with future returns should be zero:

$$\begin{aligned}\sum_{i=1}^{N_p} \operatorname{cov}(\omega_{it}, r_{i,t+1}) &= \sum_{i=1}^{N_p} E[(\omega_{it} - E[\omega_i])(r_{i,t+1} - E[r_i])] \\ &= \sum_{i=1}^{N_p} E[\omega_{it}(r_{i,t+1} - E[r_i])] = 0,\end{aligned} \tag{9}$$

where ω_{it} is the portfolio weight of asset i selected at time t and held from time t through $t + 1$. Insiders with superior information will generate a positive estimate of equation (9) because they are able to correlate this period's trade with next period's return. Grinblatt and Titman (1989), in the context of managed portfolios, demonstrate that a risk-averse manager with superior information will generate a positive estimate of the covariance measure (9) if the manager's level of Rubinstein (1973) absolute risk aversion is nonincreasing.

In the presence of nonconstant expected returns, the covariance in equation (9) will exhibit a bias when investors have no superior information, but use publicly available information to forecast returns and trade on these forecasts. To avoid this potential bias, we extend equation (9) to a conditional setting:

$$\sum_{i=1}^{N_p} \operatorname{cov}(\omega_{it}, r_{i,t+1} | Z_t^*) = \sum_{i=1}^{N_p} E[\omega_{it}(r_{i,t+1} - E[r_{i,t+1} | Z_t^*]) | Z_t^*]. \tag{10}$$

The conditional covariance in equation (10) measures whether a manager's portfolio weights are correlated with the unforecastable portion of portfolio returns, where the forecasts use only Z_t^*.[6]

We estimate equation (10) as follows: Let $\mathbf{r_{p,t+1}}$ denote the $(N_p \times 1)$ vector of excess returns and $\boldsymbol{\omega}_{\mathbf{pt}}$ the $(N_p \times 1)$ vector of portfolio weights. Moreover, define

$$\mathbf{u1_{p,t+1}} = \mathbf{r_{p,t+1}} - \Delta_{\mathbf{p}}' \mathbf{Z_t} \tag{11}$$

$$u2_{p,t+1} = \boldsymbol{\omega}_{\mathbf{pt}}' \mathbf{u1_{p,t+1}} - \Phi_p, \tag{12}$$

with the following orthogonality restrictions:

$$E(\mathbf{u1_{p,t+1}} \mathbf{Z_t'}, u2_{p,t+1} \mathbf{Z_t}) = 0. \tag{13}$$

The $N_p \times 1$ vector $\mathbf{u1_{p,t+1}}$ when multiplied by $\mathbf{Z_t}$ forms a set of seemingly unrelated regressions of the asset returns from the portfolio on the time t information set, producing estimates of the parameters summarized in the $N_p \times L$ matrix $\boldsymbol{\Delta}_{\mathbf{p}}$. The GMM estimate of the parameter Φ_p is an average of the conditional covariance of equation (10). The second term in equation (13) imposes the restriction that this covariance be orthogonal to the information set Z_t.

We now turn to the empirical analysis of the three performance measures $\mu_{\mathbf{p}}$, α_p, and Φ_p, applied to portfolios of insider stock holdings as well as to managed mutual funds.

II. Data and Sample Characteristics

A. *Insider Trades and Holdings*

Our empirical analysis focuses on all individuals defined as "insiders" according to the 1985 amendment to the Norwegian Securities Trading Act. The definition of an insider includes the CEO, the top managers of the firm, members of the board of directors and supervisory boards, the firm's auditor and investment advisor, and close family members of these individuals. Each quarter, all OSE-listed firms must report to the stock exchange subsidiary, Oslo Børs Informasjon AS (OBI), all trades by each of the respective firm's insiders. The report provides the date of each insider's trade, the security traded, the trade amount, the direction of trade (purchase or sell), and the stock price per share of the transaction. The report also contains the end-of-quarter holdings of each insider in all of the firm's securities.

[6] Khang (1996), in independent work, develops a similar covariance approach to investigate mutual fund performance.

OBI supplied us with a database that contains (i) the complete set of 18,301 insider trade records in 247 securities (197 companies) from January 1985 through December 1992, and (ii) the last reported holding records for the population of 24,369 insiders as of December 1992. As explained below, we use this information to reconstruct a monthly time series of each insider's holdings.

Starting with the trade information, the average security has 96 insiders trading a total of 80 times over the sample period. Of the total number of registered insiders, 21 percent traded at least once during the sample period. Thus, the 18,301 trade records were produced by a total of 5003 insiders trading an average of 3.7 times. Of the 79 percent of the insiders who never traded, 70 percent never held any shares in the respective companies. The identity of these insiders was nevertheless recorded by the OBI and therefore included in our database as a matter of general disclosure requirements.

Of the 18,301 trades, 35 percent are sales. Insider ownership averages 14 percent of total firm equity, and fluctuates between 10 percent and 18 percent over the sample period. The monthly change in the holdings includes a maximum net sale of approximately 1.5 percent and a maximum net purchase of approximately 1.7 percent of the company's stock. Over the sample period, insiders on average traded 26 percent of the value of their total holdings per year, representing 14 percent of the value of all trades on the OSE. In comparison, the turnover rate over the same period for the average OSE stock was 35 percent.

Turning to the OBI data on insider holdings, we recursively reconstruct from December 1992 a monthly time series of each insider's holdings by subtracting each buy and adding each sale, adjusting for changes in the firms' total number of shares outstanding caused by new security issues and stock dividends. In creating this time series, three assumptions are made. First, absent information to the contrary, we assume that insiders purchase their pro rata share of new equity issues. Second, if a firm with positive insider holdings is delisted from the exchange, we assume that the insiders' holdings are brought to zero (sold) at the end-of-month price prevailing just prior to the month of delisting. Third, at the time a shareholder becomes (or ceases to be) an insider, we do not treat the implied change in insider holdings as an insider buy (or sell).

The individual insider shareholdings are used to form a portfolio of aggregate insider holdings, using the portfolio weight defined above in equations (1) and (2) in Section I. Given a vector of portfolio weights $\omega_{\mathbf{pt}} = (\omega_{1t}, \omega_{2t}, \ldots, \omega_{it}, \ldots, \omega_{N_{pt}})'$, we construct the monthly excess return on the insider portfolio as

$$r_{p,t+1} \equiv \sum_{i=1}^{N_p} \omega_{it} r_{i,t+1},$$

where $r_{i,t+1}$ is security i's return over month $t+1$ in excess of the risk-free rate. Monthly returns and prices are provided by OBI.

The number of insider records used in the subsequent empirical analysis is slightly smaller than the population provided by the OBI. We discovered 95 duplicate trade records, 18 missing trade records, as well as missing holding records for 71 insiders. Moreover, of the 247 listed securities in the database, 17 had zero insider holdings over the entire sample period. Thus, the total number of securities with insider trades is 230. The total number of firms listed in our data set in a given month varies from a low of 99 to a high of 131 over the sample period, with an average of 116.

B. Mutual Funds

We select the seven largest mutual funds in Norway for which we could find complete data on portfolio weights between 1985 and 1992.[7] The seven funds are Avanse (AVEM), Avanse Spar (SPIM), Kreditkassen K-Avkasting (KAGM), Kreditkassen K-Vekst (KVTM), G-Aksjefond (NAKM), UNI-finans (NOFM), and UNI-Pluss (NOPM). For each fund, we calculate the monthly change in the value of the fund including any dividend paid on the fund.

Mutual fund portfolio weights are collected from the periodic reports sent to fund customers. In Norway, fund companies are required to report portfolio weights three times a year: at the end of April, August, and December. Similarly to Grinblatt and Titman (1993), we assume that mutual fund managers revise their portfolios with the same frequency as the reporting requirement.

C. Risk Factors, Factor-Mimicking Portfolios, and Information Variables

As listed in Table I, the empirical analysis employs three risk factors. The first is the excess (world) market return, *dxmsci*, represented by the with-dividend monthly change in the Morgan Stanley Capital Index (MSCI) (measured in Norwegian Kroner (NOK)) less the monthly yield on the three-month Norwegian Interbank Offer rate (NIBOR). The MSCI represents the value-weighted level of 19 OECD stock markets plus Singapore/Malaysia and Hong Kong. Harvey (1991) shows that the MSCI return dominates many country proxies (including the U.S. New York Stock Exchange index) in the sense of having higher average historical returns per unit of variance.

The second and third risk variables are the factor-mimicking portfolios for the changes in the term structure, *dterm*, and the real interest rate, *nibor*. These capture the effects on the discounted value of future cash flows of both the level of real short term rates and the term structure. Merton (1973) develops a model in which the interest rate level enters as a state pricing variable. Ferson and Harvey (1991, 1993) use the real interest rate as a pricing variable in studies on U.S. and international data. Chen, Roll, and

[7] By selecting the largest surviving funds, we are inducing a positive bias in our performance measurement of the mutual funds. We return to this issue in Section IV.

Ross (1986) find that changes in the term structure are priced in cross-sectional tests of U.S. stock return portfolios.[8]

The term structure variable *dterm* is measured as the change in the difference between the average monthly yield on Norwegian government long-term bonds and the average monthly yield on the three-month NIBOR. The real interest rate *nibor* is the level of the monthly NIBOR yield in excess of the change in the Norwegian CPI. Because these two factors are not traded assets, one cannot strictly interpret the fitted values $\hat{\gamma}'\mathbf{Z_t}$ from equation (5) as estimates of the ex ante factor risk premia. These factors should be represented by portfolios of traded assets, or factor mimicking portfolios (see, e.g., Shanken (1992)). We form factor mimicking portfolios from linear combinations of size-based decile portfolios on the OSE using the procedure developed by Breeden, Gibbons, and Litzenberger (1989). This involves regressing the interest rate variables on the decile portfolio returns and the instruments in $\mathbf{Z_t}$. The mimicking portfolio weights are then constructed to be the estimates of the slope coefficients on the decile portfolios, reweighted to sum to one.[9]

The information variables in $\mathbf{Z_t}$ are expected to capture predictable variation in the portfolio returns and factor risk premia. Our choice of information variables, as listed in Table I, include the lagged values of the excess (world) market return, *dxmsci*(-1), the excess (world) market dividend yield, *xmsdiv*(-1), the real interest rate, *nibor*(-1), and a January dummy variable, *jdum*, as predictor for changes in returns through time. Ferson and Harvey (1993), Harvey (1991), and Solnik (1993) use similar variables in international cross-country comparisons.

III. The Performance of Insider Trades

Our conditional performance measures presume that the instruments in $\mathbf{Z_t}$ (described in Table I) to some extent are useful in predicting excess returns in period $t + 1$. To check this assumption, Table II reports ordinary least squares (OLS) regressions of monthly, value-weighted decile portfolio and value-weighted OSE index (TOTX) excess returns on $\mathbf{Z_t}$. The size-sorted portfolios are constructed on a monthly basis by grouping stocks into one of 10 deciles according to each stock's beginning-of-month market value. Use of

[8] For the purpose of further sensitivity analysis, we also try two alternative factor models: one using a single factor (the MSCI), and another based on five factors (the three factors reported here plus the North Sea Blend oil price index and the NOK–USD exchange rate). The results of these alternative factor models do not change the conclusions of this paper and are therefore not reported.

[9] We also construct factor-mimicking portfolios using the minimum idiosyncratic risk estimator developed in Lehmann and Modest (1988) and applied by Ferson and Korajczyk (1995). As reported in an earlier draft, use of these alternative factor mimicking portfolios does not lead to materially different conclusions.

Table I

Definitions of (Factor-Mimicking) Risk Factors, Information Variables, Insider Portfolio Weights, and Insider Subportfolios Used in the Conditional Performance Analysis

This table defines the risk factors $\mathbf{F_{t+1}}$ used to generate equilibrium risk premia in period $t+1$, and the lagged information variables $\mathbf{Z_t}$ that help predict next period's returns. Two of the three risk factors, *rnibor* and *dterm*, do not represent traded securities and are therefore replaced by factor-mimicking portfolios constructed from a linear combination of size-based decile portfolios on the OSE. The portfolio construction proceeds by regressing the nontraded factor on ten size-sorted decile portfolio returns and the instruments in $\mathbf{Z_t}$. The factor-mimicking portfolio return is then computed as the product of the decile returns and their normalized (to sum to one) slope coefficients. The insider portfolio weights, ω_{pt}, are formed at the end of period t and are used to form $r_{p,t+1}$, the insider portfolio return in period $t+1$.

Risk Factors ($\mathbf{F_{t+1}}$)	**Definition**
dxmsci	Monthly change in the Morgan Stanley Capital Index in excess of the monthly yield of the three-month NIBOR (Norwegian Interbank Offer Rate).
rnibor	Factor-mimicking portfolio representation of *nibor*, the monthly yield on the three-month NIBOR net of the monthly change in the Norwegian CPI.
dterm	Factor-mimicking portfolio representation of the monthly change in the difference between average yields on Norwegian Long Term Government Bonds (six to ten years) and the three-month NIBOR.
Information Variables ($\mathbf{Z_t}$)	**Definition**
dxmsci (−1)	*dxmsci*, lagged one period.
xmsdiv (−1)	Average monthly MSCI dividend yield, less the monthly NIBOR yield, lagged one period.
nibor (−1)	Monthly yield on three-month NIBOR net of the monthly change in the Norwegian CPI, lagged one period.
jdum	Dummy variable that equals one in the month of January and zero otherwise.
Insider Portfolio Weights ($\boldsymbol{\omega}_{\mathbf{pt}}$)	**Definition**
Value weights (ω_{it}^h)	$\omega_{it}^h \equiv h_{it}/\sum_{i=1}^{N_p} h_{it}$, where h_{it} is the total market value of insider holdings in firm i at the end of month t, and N_p is the total number of firms in the portfolio.
Ownership weights (ω_{it}^s)	$\omega_{it}^s \equiv (s_{it}/S_{it})/\sum_{i=1}^{N_p}(s_{it}/S_{it})$, where S_{it} and s_{it} denote the total number of shares outstanding and the number of shares held by insiders in firm i at the end of month t.
Insider Subportfolios	**Definition**
Large, Medium, or Small weights only	Let $c_t \equiv (\frac{1}{3})[\sup \omega_{it} - \inf \omega_{it}]$. The "Large" category contains all stocks that satisfy $\omega_{it} > \sup \omega_{it} - c_t$; The "Small" category contains all stocks satisfying $\omega_{it} < \inf \omega_{it} + c_t$ (and thus includes $\omega_{it} = 0$); and the "Medium" category contains all other stocks. Within each category, the securities are then reweighted to sum to one.

Table I—*Continued*

Large, Medium, or Small trades only	Let $c_t \equiv (\frac{1}{3})[\sup\|\Delta\omega_{it}\| - \inf\|\Delta\omega_{it}\|]$, where $\Delta\omega_{it} \equiv \omega_{it} - \omega_{i,t-1}$ (the change in insider holdings in stock i from $t-1$ to t). Stocks are placed in each of the three categories using an allocation rule analogous to the one shown above for the Large, Medium, and Small weights categories, with the additional constraint that stocks with no trade ($\Delta\omega_{it} = 0$) are excluded.
Buys (sales) only	A portfolio that at each date t restricts $\Delta\omega_{it} \equiv \omega_{it} - \omega_{i,t-1} > 0$ ($\Delta\omega_{it} < 0$ for "sales only").

size-sorted portfolios is motivated by the assumption that size (when measured by market value) may proxy for risk.[10]

As shown in Table II, a significant amount of the variation in the value-weighted excess return can in fact be explained by the instruments in $\mathbf{Z_t}$. The adjusted R^2 is 6.9 percent and the p-value associated with the hypothesis that none of the return variation is explained by our instrument choice is well below 5 percent. A similar pattern persists across the size decile excess returns, particularly for portfolios of larger-cap stocks: four of the ten portfolios have p-values well below 5 percent. Across all portfolios, the lagged return on the MSCI world market index appears to be the most important explanatory variable. With this diagnostic check on the predictive power of $\mathbf{Z_t}$, we now turn to the performance estimation.

A. Conditional Event Study Approach

Given the importance of event studies in the empirical literature on insider trades, we begin our performance analysis using the event-study approach. Table III reports average abnormal return estimates for a seven-month event window ($W = 7$) estimated using equation (4). As described in Section I.B, the estimation procedure yields a total of E vectors $\hat{\boldsymbol{\mu}}_{\mathbf{e_p}}$, $p = 1,\ldots,E$, each containing the seven monthly abnormal return estimates for the respective portfolios. Portfolio p is formed using all firms in calendar month e_p that have nonzero net insider trades in that month. We follow Seyhun (1986) and define a firm with nonzero net trades as one where the number of insiders buying the firm's shares is different from the number of insiders selling. Portfolio abnormal returns are then estimated for month e_p (event month 0) through month $e_p + 6$ (event month 6) always using $T = 48$ monthly return observations ending in month $e_p + 6$. The table reports the average value of $\hat{\boldsymbol{\mu}}_{\mathbf{e_p}}$, as well as the p-value for this average. To illustrate, let $\hat{\mu}_{e_p,0}$ denote the first element of the vector $\hat{\boldsymbol{\mu}}_{\mathbf{e_p}}$, that is, the estimated abnormal return over

[10] See Berk (1995) for a motivation of this assumption within an equilibrium framework.

Table II

The Predictability of the Decile Portfolio Returns: Oslo Stock Exchange, January 1985 to December 1992

This table reports OLS-estimates of the coefficients δ_p in the following regression:

$$r_{p,t+1} = \delta_{\mathbf{p}}' \mathbf{Z_t} + \epsilon_{\mathbf{p,t+1}},$$

where $r_{p,t+1}$ is the excess portfolio return on the value-weighted OSE market index (TOTX) and ten size-sorted decile portfolios (sorted on beginning-of-month market values and where decile 1 contains the largest market value stocks), respectively. $\mathbf{Z_t}$ contains the (one-period) lagged information variables (see Table I), plus a constant. The regressions use 96 monthly observations. The last column reports the adjusted R^2 and p-values for the hypothesis that the four slope coefficients are jointly equal to zero. The test statistic is distributed as an F-statistic with (4,91) degree of freedom. The p-values for the coefficient estimates, which are given in parentheses, are computed using White's (1980) heteroskedastic-consistent estimator for standard errors.

Portfolio	*Intercept* δ_0	*dxmsci(−1)* δ_1	*xmsdiv(−1)* δ_2	*nibor(−1)* δ_3	*jdum* δ_4	Adj. R^2
TOTX	0.049	−3.414	0.202	0.100	0.043	0.069
	(0.088)	(0.019)	(0.234)	(0.959)	(0.149)	(0.032)
Decile 1	0.040	−2.845	0.205	0.330	0.028	0.027
	(0.235)	(0.071)	(0.277)	(0.884)	(0.310)	(0.164)
Decile 2	0.064	−4.812	0.262	0.929	0.060	0.109
	(0.052)	(0.005)	(0.097)	(0.649)	(0.123)	(0.006)
Decile 3	0.067	−4.510	0.292	−0.797	0.055	0.109
	(0.024)	(0.005)	(0.095)	(0.668)	(0.124)	(0.006)
Decile 4	0.048	−3.556	0.251	−0.579	0.055	0.117
	(0.084)	(0.012)	(0.011)	(0.740)	(0.044)	(0.004)
Decile 5	0.044	−3.550	0.110	−1.117	0.056	0.058
	(0.089)	(0.019)	(0.447)	(0.454)	(0.142)	(0.050)
Decile 6	0.032	−2.622	0.133	−0.795	0.038	0.032
	(0.198)	(0.075)	(0.431)	(0.597)	(0.142)	(0.141)
Decile 7	0.010	−1.128	0.270	−0.633	0.018	0.031
	(0.674)	(0.395)	(0.067)	(0.662)	(0.358)	(0.142)
Decile 8	0.014	−1.818	0.147	−0.874	0.050	0.020
	(0.600)	(0.193)	(0.349)	(0.645)	(0.021)	(0.210)
Decile 9	0.010	−1.296	0.145	−2.094	0.033	0.010
	(0.679)	(0.307)	(0.286)	(0.182)	(0.111)	(0.297)
Decile 10	0.040	−2.573	0.079	−0.013	0.050	0.027
	(0.113)	(0.078)	(0.670)	(0.994)	(0.097)	(0.164)

event month 0 for portfolio p. The average abnormal return for event month zero reported in Table III is then given by

$$\hat{\mu}_0 = (1/E) \sum_{p=1}^{E} \hat{\mu}_{e_p,0}.$$

Moreover, the reported p-value is for the z-statistic

$$z \equiv (1/\sqrt{E}) \sum_{p=1}^{E} (\hat{\mu}_{e_p,0}/\sigma_{e_p,0}),$$

where $\boldsymbol{\sigma}_{\mathbf{e_p,0}}$ is the estimated standard error of $\hat{\mu}_{e_p,0}$. This z-statistic is distributed asymptotically standard normal.

Panel A of Table III reports average abnormal returns from estimates of equation (4) for the case where the vector of risk factors $\mathbf{F_t}$ only contains the market index (TOTX) and where the vector of instruments $\mathbf{Z_t}$ is reduced to a constant. As a result, this specification corresponds to the single-factor, unconditional market model often used in event studies, including Seyhun (1986). Panels B and C give the average abnormal return estimates from equation (4) using all of the risk and information variables and weighting the returns in the portfolios by insider holdings in event month 0. Note again that, in contrast to the conditional Jensen's alpha and portfolio weight approaches, these portfolio weights are kept fixed throughout the estimation period. Each panel reports results for portfolios of net buys only, net sales only, and for all trades.

Table III shows that, regardless of the benchmark return model and the portfolio weighting scheme, firms with net insider *buys* generally exhibit statistically insignificant abnormal stock returns in the month of trade and over the following six-month period. When abnormal returns are estimated using the single-factor, unconditional market model, however, firms with net insider *sales* exhibit statistically significant abnormal returns. The abnormal returns are significantly *positive* in month zero, suggesting that insiders sell just prior to price increases, and they are significantly *negative* over months 1 through 4, indicating subsequent abnormal price declines. Because we are using monthly return observations, it is possible that the positive abnormal return in month 0 in part occurs prior to the actual trade that month, as reported by Seyhun (1986) as well.[11] Regardless, as seen from the parameter values in Panel A, the abnormal price decline in months 1 through 4 exceeds the positive month 0 abnormal return, which is consistent with the hypothesis that these insider sales reflect information not yet reflected in stock prices.

However, the results of Panels B and C in Table III also suggest that the abnormal returns in Panel A are largely an artifact of the methodology itself. Modifying the unconditional one-factor model to allow for a conditional multifactor return generating process, as well as giving larger trades a greater than equal weight, eliminates virtually all the evidence of superior performance in months following the event month. Although not shown in

[11] Seyhun (1986) reports average cumulative abnormal returns of 1.7 percent over the 20 days just prior to insider sales, followed by negative average abnormal returns of −0.9 percent over the subsequent 20 days.

Table III

Average Monthly Abnormal Returns to Insider Trades: Conditional Event Study Approach, Oslo Stock Exchange, January 1985 to December 1992

This table reports average monthly abnormal returns relative to the month of insider trades (month 0), estimated as event parameters μ in the following model:

$$r_{p,t+1} = a_p + \mathbf{b}_\mathbf{p}'(\mathbf{F_{t+1}} \otimes \mathbf{Z_t}) + \boldsymbol{\mu}_{\mathbf{e_p}}'\mathbf{D_{p,t+1}} + \epsilon_{p,t+1},$$

where $\mathbf{b_p}$ is a $(KL \times 1)$ vector of coefficients associated with time-varying risk parameters (including a constant term), and $\mathbf{D_{p,t+1}}$ is a $(W \times 1)$ vector of zeros and ones. The total event window is seven months ($W = 7$), starting with the month of the insider trade, thus $\boldsymbol{\mu}_{\mathbf{e_p}}$ is a (7×1) vector of abnormal return coefficients, one for each of seven months. When $t + 1$ is outside the event window, $\mathbf{D_{p,t+1}}$ is a vector of zeros. When $t + 1$ is inside the event window, $\mathbf{D_{p,t+1}}$ contains zeros and the value 1 for the corresponding month in the event window. The estimation proceeds in a standard event-study fashion: Let e_1 be the first calendar month in the insider trading sample period (January 1985), and form a fixed-weight portfolio of all firms with nonzero net insider trading in that month (defined as the number of insiders buying being different from the number of insiders selling). Label e_1 "event month 0 for portfolio 1." The excess return of portfolio 1 is regressed using the above equation and a total of $T = 48$ months starting in event month $e_1 - (T - W)$. The regression yields a vector of estimates of the event parameters for months e_1 through $e_1 + W - 1$, denoted $\hat{\boldsymbol{\mu}}_{\mathbf{e_1}}$. Moving forward to the next month with nonzero net insider trades, denoted e_2 (event month 0 for portfolio 2), the regression is repeated, yielding a second vector of estimates $\hat{\boldsymbol{\mu}}_{\mathbf{e_2}}$. Over the entire sample period, this yields a total of E vectors of event parameter estimates $\hat{\boldsymbol{\mu}}_{\mathbf{e_p}}, p = 1, \ldots, E$, that is, one vector for each of the E portfolios. The table reports the average value of $\hat{\boldsymbol{\mu}}_{\mathbf{e_p}}$ across the E portfolios, as well as the p-value for this average (in parentheses). Each panel reports estimates for three portfolios: the "All trades" portfolio, which does not condition on the net direction of the trades, and the "Net buys only" and the "Net sales only" portfolios, which are restricted to firms where the number of insiders buying were greater or smaller than the number of insiders selling, respectively. In Panel A, portfolios are equal weighted and the unconditional one-factor model uses the excess return on the OSE total market index as the only factor. Panels B and C use the full conditional multifactor model with either value-weighting of portfolios (Panel B) or with portfolios formed using ownership weights. (See Table I for definitions of $\mathbf{F_{t+1}}$, $\mathbf{Z_t}$, and the value- and ownership weights.)

	Average Monthly Abnormal Return, $\hat{\mu}_i$, i = month 0, …, month 6 (p-value)						
Type of Trade	$\hat{\mu}_0$	$\hat{\mu}_1$	$\hat{\mu}_2$	$\hat{\mu}_3$	$\hat{\mu}_4$	$\hat{\mu}_5$	$\hat{\mu}_6$
Panel A: Unconditional One-Factor Market Model with Equal Weights							
All trades	−0.004	−0.012	−0.020	−0.018	−0.027	−0.017	−0.010
	(0.102)	(0.328)	(0.033)	(0.024)	(0.014)	(0.153)	(0.492)
Net buys only	−0.015	−0.009	−0.022	−0.015	−0.014	−0.024	−0.009
	(0.421)	(0.926)	(0.145)	(0.421)	(0.626)	(0.045)	(0.768)
Net sales only	0.008	−0.015	−0.018	−0.021	−0.040	−0.010	−0.011
	(0.001)	(0.088)	(0.165)	(0.050)	(0.000)	(0.213)	(0.933)
Panel B: Conditional Multifactor Model with Value Weights (ω_{it}^h)							
All trades	0.019	0.013	0.007	−0.002	−0.007	0.007	0.018
	(0.152)	(0.336)	(0.554)	(0.608)	(0.965)	(0.472)	(0.282)
Net buys only	0.004	0.008	0.008	0.009	−0.018	0.023	0.023
	(0.556)	(0.508)	(0.761)	(0.219)	(0.679)	(0.264)	(0.453)
Net sales only	0.035	0.018	0.005	−0.012	0.004	−0.009	0.013
	(0.029)	(0.418)	(0.643)	(0.642)	(0.707)	(0.982)	(0.249)

Table III—*Continued*

	Average Monthly Abnormal Return, $\hat{\mu}_i$, i = month 0, …, month 6 (p-value)						
Type of Trade	$\hat{\mu}_0$	$\hat{\mu}_1$	$\hat{\mu}_2$	$\hat{\mu}_3$	$\hat{\mu}_4$	$\hat{\mu}_5$	$\hat{\mu}_6$
Panel C: Conditional Multifactor Model with Ownership Weights (ω_{it}^s)							
All trades	0.051	0.013	0.001	−0.003	0.009	0.015	0.040
	(0.002)	(0.312)	(0.940)	(0.745)	(0.557)	(0.763)	(0.084)
Net buys only	0.005	0.024	−0.010	−0.004	−0.012	0.015	0.029
	(0.848)	(0.323)	(0.703)	(0.685)	(0.961)	(0.669)	(0.380)
Net sales only	0.097	0.003	0.013	−0.001	0.031	0.015	0.050
	(0.000)	(0.898)	(0.591)	(0.991)	(0.294)	(0.867)	(0.072)

Table III, separate analysis shows that both of these two econometric modifications contribute to the reduction of the abnormal return evidence in Panel A. In sum, using the conditional event-study approach, net insider sales underperform in month zero but we cannot reject the hypothesis of zero abnormal performance in the six-month period following the month of trade.

B. Conditional Jensen's Alpha

As a diagnostic check, we begin by applying the conditional asset pricing system (5) through (7) to a set of nonmanaged portfolios on the OSE. Because nonmanaged portfolios do not reflect nonpublic information, they should produce estimates of Jensen's alpha equal to zero. As shown in Table IV, the nonmanaged portfolios are the same as in Table II, that is, the total OSE market index and the ten size-based decile portfolios. Table IV reports estimates of α_p, which allows for time-varying betas and risk premia, and of α_p^*, which assumes constant conditional betas. The table also lists the constant-beta estimates for the three risk factors and Hansen's (1982) goodness-of-fit test. Recall from Section I (footnote 5) that this goodness-of-fit test can be interpreted as a test for the hypothesis of constant conditional betas against the alternative that the betas vary according to $\boldsymbol{\kappa}_{\mathbf{p}}'\mathbf{Z_t}$.

According to the goodness-of-fit statistic, we cannot reject the hypothesis of constant conditional betas for any of the 11 portfolios in Table IV. Focusing on the OSE index (TOTX), the constant beta estimates in Table IV are positive and significant for the world stock market return *dxmsci* and the real interest rate *rnibor*, and positive but insignificant for the term structure factor *dterm*. The latter risk factor does receive, however, a significant constant-beta estimate for 9 of the 10 decile portfolios. Importantly, the estimates of α_p and α_p^* are small and similar in magnitude across portfolios, and of the 22 alpha estimates only 1 is significant at the 5 percent level or better. Coupled with uniformly low values for the goodness-of-fit test statistic, we cannot reject the hypothesis that the conditional asset pricing model specification is valid for the OSE.

Table IV

GMM Estimates of a Conditional Asset Pricing Model for the Oslo Stock Exchange, January 1985 to December 1992

This table reports GMM estimates of the conditional abnormal performance measure α_p using the following system of equations:

$$\mathbf{u1_{p,t+1}} = \mathbf{F_{t+1}} - \gamma_{\mathbf{p}}' \mathbf{Z_t}$$

$$\mathbf{u2_{p,t+1}} = (\mathbf{u1_{p,t+1}} \mathbf{u1'_{p,t+1}})(\kappa_{\mathbf{p}}' \mathbf{Z_t}) - \mathbf{u1_{p,t+1}} r_{p,t+1}$$

$$u3_{p,t+1} = r_{p,t+1} - \alpha_p - (\gamma_{\mathbf{p}}' \mathbf{Z_t})'(\kappa_{\mathbf{p}}' \mathbf{Z_t}),$$

where $r_{p,t+1}$ is the excess return on portfolio p in month $t+1$, $\mathbf{Z_t}$ is the set of information variables (including a constant), and $\mathbf{F_{t+1}}$ is the set of risk factors (see Table I). The table also reports the estimate α_p^* obtained by constraining the conditional betas to be constant (i.e., imposing $\kappa_{\mathbf{p}}' = (\kappa_{\mathbf{p0}}, \mathbf{0}, \ldots, \mathbf{0})$, where $\kappa_{\mathbf{p0}}$ is a $K \times 1$ vector of coefficients and $\mathbf{0}$ is a K-vector of zeros), as well as the constant beta estimates. TOTX is the total value-weighted OSE index, and Decile 1 contains the largest-value (size-sorted) stocks. Asymptotic p-values are in parentheses. Hansen's (1982) goodness-of-fit test statistic, which is asymptotically distributed $\chi^2(12)$, is used to test the following $R = (2KL + 1)$ sample orthogonality conditions under the restriction of constant conditional betas: $E(\mathbf{u1_{p,t+1}} \mathbf{Z_t'}, \mathbf{u2_{p,t+1}} \mathbf{Z_t'}, u3_{p,t+1}) = 0$, where $K = 3$ is the number of factors and $L = 5$ is the number of information variables (including a constant).

Portfolio	Mean Monthly Raw Return [Std. dev.]	$\hat{\alpha}_p$	$\hat{\alpha}_p^*$	Constant Beta Estimates: *dxmsci*	*rnibor*	*dterm*	Goodness-of-Fit Test
TOTX	0.006	0.007	0.005	0.583	0.162	0.119	9.220
	[0.070]	(0.237)	(0.353)	(0.001)	(0.050)	(0.114)	(0.684)
Decile 1	0.007	0.005	0.005	0.702	0.169	−0.012	11.134
	[0.074]	(0.433)	(0.422)	(0.000)	(0.056)	(0.879)	(0.517)
Decile 2	0.005	0.009	0.007	0.657	−0.031	0.442	8.094
	[0.085]	(0.175)	(0.303)	(0.001)	(0.727)	(0.000)	(0.778)
Decile 3	0.002	0.005	0.004	0.637	0.269	0.262	5.372
	[0.079]	(0.431)	(0.439)	(0.001)	(0.001)	(0.001)	(0.944)
Decile 4	0.000	0.007	0.004	0.395	0.463	0.159	8.095
	[0.067]	(0.093)	(0.277)	(0.001)	(0.000)	(0.010)	(0.778)
Decile 5	−0.007	−0.004	−0.005	0.332	0.269	0.272	11.403
	[0.073]	(0.462)	(0.329)	(0.008)	(0.001)	(0.001)	(0.495)
Decile 6	−0.003	0.004	0.007	0.357	0.103	0.547	11.318
	[0.065]	(0.376)	(0.098)	(0.000)	(0.006)	(0.000)	(0.502)
Decile 7	−0.001	0.002	0.001	0.271	0.147	0.349	7.383
	[0.058]	(0.733)	(0.824)	(0.013)	(0.035)	(0.000)	(0.831)
Decile 8	−0.008	0.003	0.001	0.162	0.175	0.519	11.804
	[0.072]	(0.569)	(0.902)	(0.107)	(0.004)	(0.000)	(0.462)
Decile 9	−0.012	−0.008	−0.007	0.085	−0.015	0.431	10.876
	[0.063]	(0.097)	(0.068)	(0.331)	(0.780)	(0.000)	(0.540)
Decile 10	0.011	0.013	0.011	0.240	0.100	0.316	4.437
	[0.072]	(0.047)	(0.083)	(0.030)	(0.209)	(0.001)	(0.974)

Table V, which has the same basic format as Table IV, reports estimates of Jensen's conditional α_p and α_p^* and constant conditional beta estimates for portfolios of insider holdings and trades. Panel A shows estimates for value-weighted portfolios (ω_{it}^h); Panel B shows estimates for portfolios weighted by insider ownership proportions (ω_{it}^{s}). Each panel shows results for the portfolio containing all securities held by insiders as well as for eight subportfolios selected using trade and holding characteristics. As discussed below, the purpose of these subportfolios is to indicate to what extent insider performance is sensitive to the size of the insider holding as well as to the size and direction of the trade.

As shown in Table I, the eight subportfolios are formed using the size of the insider's holding (small, medium, and large), the size of the insider's trade (small, medium, and large), as well as whether the transaction was a purchase or a sale. The break points at each date t that define the three "Large-," "Medium-," and "Small weights only" portfolios are constructed using $c_t \equiv (\frac{1}{3})[\sup \omega_{it} - \inf \omega_{it}]$ (where "sup" and "inf" denote the maximum and minimum values, respectively, of the portfolio weights in a given month). The "Large" category contains all stocks that satisfy $\omega_{it} > \sup \omega_{it} - c_t$. The "Small" category contains all stocks satisfying $\omega_{it} < \inf \omega_{it} + c_t$ (and thus includes $\omega_{it} = 0$), and the "Medium" category contains all other stocks. Within each category, the securities are then reweighted to sum to one.

Similarly, the three "Large-," "Medium-," and "Small trades only" portfolios are formed using $c_t \equiv (\frac{1}{3})[\sup|\Delta\omega_{it}| - \inf|\Delta\omega_{it}|]$, where $\Delta\omega_{it} \equiv \omega_{it} - \omega_{i,t-1}$ (the change in insider holdings in stock i from $t-1$ to t). Stocks are then put in each of the three categories using an allocation rule analogous to the one shown above for the "Large-," "Medium-," and "Small weights only" categories, with the additional constraint that stocks with no trade ($\Delta\omega_{it} = 0$) are excluded. Furthermore, the remaining two trade-based subportfolios, "Buys only" and "Sales only," are formed at each date t according to whether $\Delta\omega_{it}$ is strictly positive or negative.

As indicated earlier, the "All securities" portfolio fully tracks the trades of insiders in and out of the stocks and thus yields the average monthly abnormal performance over the insiders' *actual* holding period. The subportfolios, however, restrict on a month-by-month basis the weights relative to the "All securities" portfolio. For example, in the "weights" category, the "Large weights only" portfolio measures the average monthly performance using only the months where insiders' weights in the firm are "Large." Note that this average monthly performance reflects an insider holding period that extends beyond one month whenever insider ownership remains "Large" for several periods. Finally, in the "trades" category, performance is measured over a one-month holding period following the month of the trade. For example, the "Large trades only" portfolio measures the average monthly performance using only the months where insiders traded *and* where the trade is "Large." By excluding nontrading periods, the trade-based subportfolios also have a conditional event-study interpretation, where the event window consists of the month following the trade only.

The "All securities" estimates of α_p in both Panels A and B of Table V suggest that across the entire set of securities, both value- and ownership-weighted insider portfolios earn abnormal returns that are statistically indistinguishable from zero. This result holds whether we estimate abnormal performance using constant conditional betas or the more general, time-varying beta model.

Table V

GMM Estimates of a Conditional Asset Pricing Model Benchmark Applied to Portfolios of Insider Holdings on the Oslo Stock Exchange, January 1985 to December 1992

This table reports GMM estimates of the conditional abnormal performance measure α_p using the following system of equations:

$$\mathbf{u1_{p,t+1}} = \mathbf{F_{t+1}} - \boldsymbol{\gamma}'_{\mathbf{p}}\mathbf{Z_t}$$

$$\mathbf{u2_{p,t+1}} = (\mathbf{u1_{p,t+1}}\mathbf{u1'_{p,t+1}})(\kappa'_{\mathbf{p}}\mathbf{Z_t}) - \mathbf{u1_{p,t+1}} r_{p,t+1}$$

$$u3_{p,t+1} = r_{p,t+1} - \alpha_p - (\gamma'_{\mathbf{p}}\mathbf{Z_t})'(\kappa'_{\mathbf{p}}\mathbf{Z_t}),$$

where $r_{p,t+1}$ is the excess return on portfolio p in month $t+1$, $\mathbf{Z_t}$ is the set of information variables (including a constant) and $\mathbf{F_{t+1}}$ is the set of risk factors. The table also reports the estimate α_p^* obtained by constraining the conditional betas to be constant (i.e., imposing $\kappa'_{\mathbf{p}} = (\kappa_{\mathbf{p0}},\mathbf{0},\ldots,\mathbf{0})$, where $\kappa_{\mathbf{p0}}$ is a $K \times 1$ vector of coefficients and $\mathbf{0}$ is a K-vector of zeros), as well as the constant beta estimates. See Table I for definitions of $\mathbf{F_{t+1}},\mathbf{Z_t}$, the portfolio weights, and the various insider subportfolios. Panel A reports results for portfolios formed using value weights; Panel B utilizes ownership weights. Asymptotic p-values are in parentheses. Hansen's (1982) goodness-of-fit test statistic, which is asymptotically distributed $\chi^2(12)$, is used to test the following $R = (2KL + 1)$ sample orthogonality conditions under the restriction of constant conditional betas: $E(\mathbf{u1_{p,t+1}}\mathbf{Z'_t},\mathbf{u2_{p,t+1}}\mathbf{Z'_t},u3_{p,t+1}) = 0$, with $K = 3$ and $L = 5$.

Portfolio	Mean Monthly Raw Return [Std. dev.]	$\hat{\alpha}_p$	$\hat{\alpha}_p^*$	Constant Beta Estimates *dxmsci*	*rnibor*	*dterm*	Goodness-of-Fit Test
Panel A: Portfolios Formed Using Value Weights (ω_{it}^h)							
All securities	−0.005	−0.001	−0.011	0.558	0.160	0.205	12.321
	[0.073]	(0.893)	(0.079)	(0.002)	(0.055)	(0.003)	(0.420)
Large weights	−0.018	−0.007	−0.030	0.748	0.327	−0.059	11.249
only	[0.119]	(0.575)	(0.005)	(0.003)	(0.005)	(0.633)	(0.508)
Medium weights	−0.012	−0.019	−0.015	0.434	0.004	0.251	3.807
only	[0.085]	(0.036)	(0.073)	(0.004)	(0.973)	(0.011)	(0.926)
Small weights	0.002	0.005	0.007	0.578	0.205	0.346	8.210
only	[0.069]	(0.405)	(0.189)	(0.000)	(0.006)	(0.000)	(0.769)
Large trades	0.018	0.031	0.015	0.782	0.093	0.603	14.644
only	[0.209]	(0.148)	(0.352)	(0.015)	(0.557)	(0.011)	(0.261)
Medium trades	0.002	0.002	−0.008	−0.019	−0.052	0.115	12.233
only	[0.071]	(0.820)	(0.139)	(0.831)	(0.426)	(0.131)	(0.427)
Small trades	−0.005	−0.002	−0.009	0.439	0.159	0.227	9.950
only	[0.071]	(0.808)	(0.124)	(0.008)	(0.056)	(0.004)	(0.620)
Buys only	−0.012	−0.010	−0.017	0.621	0.269	0.179	7.849
	[0.089]	(0.240)	(0.022)	(0.006)	(0.010)	(0.028)	(0.797)
Sales only	0.002	−0.004	−0.001	0.752	0.305	−0.009	7.578
	[0.091]	(0.639)	(0.910)	(0.000)	(0.004)	(0.891)	(0.817)

Table V—*Continued*

Portfolio	Mean Monthly Raw Return [Std. dev.]	$\hat{\alpha}_p$	$\hat{\alpha}_p^*$	Constant Beta Estimates *dxmsci*	Constant Beta Estimates *rnibor*	Constant Beta Estimates *dterm*	Goodness-of-Fit Test
Panel B: Portfolios Formed Using Ownership Weights (ω_{it}^s)							
All securities	−0.010	−0.010	−0.008	−0.266	0.315	0.330	16.293
	[0.108]	(0.389)	(0.466)	(0.099)	(0.003)	(0.005)	(0.178)
Large weights only	−0.034	−0.029	−0.053	−0.051	0.347	0.139	17.958
	[0.201]	(0.131)	(0.007)	(0.894)	(0.111)	(0.518)	(0.117)
Medium weights only	0.007	0.009	−0.010	0.012	0.006	0.002	14.883
	[0.101]	(0.459)	(0.004)	(0.494)	(0.743)	(0.947)	(0.295)
Small weights only	0.008	0.009	0.001	0.366	−0.032	0.327	4.698
	[0.077]	(0.367)	(0.924)	(0.000)	(0.589)	(0.000)	(0.967)
Large trades only	0.004	−0.004	−0.019	0.255	−0.077	0.348	9.020
	[0.185]	(0.823)	(0.105)	(0.191)	(0.662)	(0.090)	(0.701)
Medium trades only	−0.007	−0.002	−0.009	0.065	0.034	0.060	13.017
	[0.099]	(0.847)	(0.083)	(0.698)	(0.589)	(0.288)	(0.368)
Small trades only	−0.014	−0.011	−0.012	−0.102	0.134	0.428	12.451
	[0.103]	(0.312)	(0.206)	(0.519)	(0.112)	(0.002)	(0.410)
Buys only	−0.006	0.003	−0.007	0.064	0.259	0.348	17.307
	[0.160]	(0.855)	(0.501)	(0.804)	(0.131)	(0.062)	(0.138)
Sales only	−0.009	−0.012	−0.016	0.449	0.329	−0.088	7.681
	[0.083]	(0.126)	(0.020)	(0.009)	(0.005)	(0.305)	(0.681)

Focusing on the estimates of α_p^* formed assuming constant conditional betas, the performance of insiders across virtually all categories is either insignificant or significantly negative. For example, when the holdings are value-weighted (Panel A), both the "Large weights only" and "Buys only" portfolios estimate α_p^* to be large and negative (−3.0 percent and −1.7 percent) and to have small p-values (0.005 and 0.022). However, when allowing conditional betas to be time-varying, the corresponding estimates of α_p are both smaller (−0.7 percent and −1.0 percent) and insignificant, with p-values of 0.575 and 0.240, respectively. On the other hand, trades in the "Medium weights only" category are significantly negative using either estimate of Jensen's alpha.

Turning to panel B of Table V, where portfolios are formed using ownership weights, the estimates of Jensen's alpha yield similar results to the value weights, with one minor exception. The "Sales only" portfolio now produces an α_p^* of −1.6 percent with a p-value of 0.020. Recall that a negative estimate of α indicates positive abnormal performance in the sales categories. However, this abnormal return disappears when the time-varying beta estimation technique is used.

Overall, the evidence in Table V rejects the hypothesis of positive insider performance. This conclusion is based on the assumption that any timing ability on the part of insiders, beyond that reflecting the publicly observable instruments $\mathbf{Z_t}$, does not induce a significant negative bias in our α estimates (as discussed in Section I.B). Given our estimation technique, the estimates of α_p^* are more likely than the estimates of α_p to exhibit such a bias, and the latter uniformly fail to reject the hypothesis of zero abnormal performance. Treynor and Mazuy (1966) propose a correction for bias due to timing ability by including the squared value of the excess market return as an additional factor in the return-generating model. Inclusion of a Treynor–Mazuy correction in the system (5) to (7) does not significantly alter our main conclusion.

C. Conditional Portfolio Weight Approach

Table VI reports values of the conditional covariance measure Φ_p of abnormal performance, estimated using portfolio weights and forecast residuals from system (11) to (12). As in Table V, we report abnormal performance estimates using both value and ownership weights, and categorize the insider portfolios according to holding and trade characteristics. The first row in Table VI shows the estimates of Φ_p for the two sets of portfolio weights over the entire sample. The estimates are -0.006 for the value weight portfolio and -0.002 for the ownership weight portfolio. Neither estimate is significantly different from zero at conventional levels of significance. In fact, insiders do not earn superior returns across any of the categories of portfolios in Table VI. All the point estimates reported in the table are small, only three have a sign consistent with superior performance, and all associated p-values exceed 10 percent.

Table VII explores the time series properties of the monthly insider performance estimates through regressions of $\omega'_{\mathbf{pt}}\hat{\mathbf{u}}\mathbf{1}_{\mathbf{p,t+1}}$ on its own lagged value ($\hat{\Phi}_{pt}$) as well as on four other variables lagged one period. The variables include a dummy for the month of January every year (*jdum*), a dummy for October through November 1987 (*crash*), the average level of insider ownership on the OSE in month t (*own*), and the change in the average level of insider ownership from month $t-1$ to t (*down*).

The lagged covariance estimate $\hat{\Phi}_{pt}$ is included to capture possible low-order dependencies in the portfolio weights not already accounted for by the instruments $\mathbf{Z_t}$. (Inclusion of higher order serial correlation and moving average representations do not alter the basic results.) The two dummy variables *jdum* and *crash* are included to capture a possible January seasonality in the covariances as well as a potential impact of the stock market crash of 1987 on subsequent covariances. The last two variables *own* and *down* are proxies for the influence of aggregate insider holdings and trades in the previous month.

The regression estimates using the value portfolio weights indicate that conditional portfolio performance tends to drop off following the month of January ($\alpha_2 = -0.038$, p-value $= 0.067$) and was lower immediately following the stock market crash of October and November 1987 ($\alpha_3 = -0.230$, p-value $= 0.000$). None of the remaining coefficient estimates are statisti-

Table VI

Conditional Portfolio Weight Measure of Performance of Portfolios of Insider Holdings on the Oslo Stock Exchange, January 1985 to December 1992

This table presents GMM estimates of Φ_p from the following system:

$$\mathbf{u1_{p,t+1}} = \mathbf{r_{p,t+1}} - \Delta'_{\mathbf{p}}\mathbf{Z_t}$$

$$u2_{p,t+1} = \omega'_{\mathbf{pt}}\mathbf{u1_{p,t+1}} - \Phi_p,$$

where $r_{p,t+1}$ is the $N_p \times 1$ vector of portfolio excess returns from t to $t+1$, $\Delta_{\mathbf{p}}$ is the $N_p \times L$ matrix of coefficients from regressing $\mathbf{r_{p,t+1}}$ on the instruments $\mathbf{Z_t}$ (including a constant), and the parameter Φ_p is the average of the conditional covariance defined in equation (7) in the text. The GMM estimation imposes the restriction that $E(\mathbf{u1_{p,t+1}}\mathbf{Z'_t}, u2_{p,t+1}\mathbf{Z_t}) = 0$. See Table I for definitions of $\mathbf{F_{t+1}}, \mathbf{Z_t}$, the portfolio weights, and the various insider subportfolios. Asymptotic p-values are in parentheses.

Portfolio	Portfolios with Value Weights (ω^h_{it})	Portfolios with Ownership Weights (ω^s_{it})
All securities	−0.006	−0.002
	(0.358)	(0.797)
Large weights only	−0.007	0.002
	(0.467)	(0.921)
Medium weights only	−0.013	−0.001
	(0.101)	(0.286)
Small weights only	−0.004	−0.002
	(0.540)	(0.766)
Large trades only	0.007	−0.001
	(0.539)	(0.964)
Medium trades only	−0.003	−0.003
	(0.379)	(0.754)
Small trades only	−0.007	−0.004
	(0.349)	(0.660)
Buys only	−0.007	−0.002
	(0.371)	(0.863)
Sales only	0.000	−0.004
	(0.988)	(0.644)

cally significant at conventional levels. This lack of significance is confirmed when using the ownership-weighted portfolio: in the second row of Table VII, none of the coefficient estimates are statistically significant.[12]

[12] Under the null hypothesis of no abnormal performance, the conditional expectation Φ_p of the cross-sectional covariances defined in equation (10) is equal to zero. However, under the alternative hypothesis, the cross-sectional covariances may vary as a function of the information set $\mathbf{Z_t}$. To investigate this possibility, we also regressed $\hat{\Phi}_{p,t+1}$ on the information variables $\mathbf{Z_t}$. The fitted values from this regression can be interpreted as estimates of the value of Φ_p conditional on $\mathbf{Z_t}$. As reported in an earlier draft of this paper, this regression fails to identify a statistical relationship between the monthly estimates of the conditional covariance and $\mathbf{Z_t}$.

Table VII

Coefficients in Regressions of Conditional Portfolio Weight Measure of Performance on Time-Series Characteristics for Insider Trades on the Oslo Stock Exchange, January 1985 to December 1992

This table presents OLS estimates of coefficients α in the following regression:

$$\hat{\Phi}_{p,t+1} = \alpha_0 + \alpha_1\hat{\Phi}_{pt} + \alpha_2 jdum_t + \alpha_3 crash_t + \alpha_4 own_t + \alpha_5 down_t + \epsilon_{p,t+1},$$

where $\hat{\Phi}_{p,t+1} \equiv \sum_{i=1}^{N_p} \omega_{it}\hat{u}1_{i,t+1}$ is the estimate of the conditional portfolio weight measure for month $t+1$, $\hat{u}1_{i,t+1}$ is the residual from the regression of the excess return on security i $r_{i,t+1}$ on the information variables $\mathbf{Z_t}$ (including a constant), ω_{it} is the portfolio weight of security i at the end of period t, and N_p is the number of securities in portfolio p. Moreover, own_t is the average shares held by insiders in the 230 securities in the sample in month t, $down_t$ is $own_t - own_{t-1}$, and $crash_t$ is a dummy variable taking on the value of one in October 1987, and zero otherwise, and $\epsilon_{p,t+1}$ is a mean zero error term. See Table I for definitions of $\mathbf{Z_t}$ and the value and ownership weights. The p-values for the coefficient estimates, which are given in parentheses, are computed using White's (1980) heteroskedastic-consistent estimator for standard errors.

Portfolio weight	α_0	α_1	α_2	α_3	α_4	α_5	Adj. R^2
Value weights (ω_{it}^h)	0.031	0.147	−0.039	−0.230	−0.215	0.835	0.102
	(0.391)	(0.175)	(0.067)	(0.000)	(0.390)	(0.515)	(0.012)
Ownership weights (ω_{it}^s)	−0.018	−0.005	−0.003	0.023	0.390	0.515	−0.054
	(0.781)	(0.968)	(0.960)	(0.498)	(0.786)	(0.753)	(0.999)

IV. A Comparison with the Performance of Mutual Funds

As indicated in the introduction, it is interesting to compare the performance of insiders to that of managed mutual funds. While neither the insider portfolio nor the mutual fund portfolios are by themselves necessarily optimal portfolios from the individual investor's point of view, their relative performance sheds light on the likelihood that the aggregate insider portfolio weights in fact reflect private information. Given the potential presence of corporate control benefits from insider holdings (which increase the costs of insider sales), as well as the decentralized nature of the insider portfolio (which prevents optimal asset allocation across individual insider holdings), it follows that for insiders to receive a higher average risk-adjusted return than mutual funds they must trade on inside information.

Table VIII presents conditional Jensen's alpha estimates for the seven mutual funds in the data base. Moreover, the table shows the alpha estimates for an equal-weighted portfolio of the seven funds, as well as for two self-financing "difference portfolios." Each difference portfolio consists of a long position in the average mutual fund portfolio and a short position in the portfolio of insider holdings (both value- and ownership-weighted). Thus, the difference portfolios allow us to directly test for differences in abnormal performance between insiders and mutual funds.

Table VIII

GMM Estimates of a Conditional Asset Pricing Model Benchmark Applied to Seven Mutual Funds on the Oslo Stock Exchange, January 1985 to December 1992

This table reports GMM estimates of the conditional abnormal performance measure α_p using the following system of equations:

$$\mathbf{u1_{p,t+1}} = \mathbf{F_{t+1}} - \gamma_\mathbf{p}'\mathbf{Z_t}$$

$$\mathbf{u2_{p,t+1}} = (\mathbf{u1_{p,t+1}}\mathbf{u1_{p,t+1}'})(\kappa_\mathbf{p}'\mathbf{Z_t}) - \mathbf{u1_{p,t+1}}r_{p,t+1}$$

$$u3_{p,t+1} = r_{p,t+1} - \alpha_p - (\gamma_\mathbf{p}'\mathbf{Z_t})'(\kappa_\mathbf{p}'\mathbf{Z_t}),$$

where $r_{p,t+1}$ is the excess return on portfolio p in month $t + 1$, $\mathbf{Z_t}$ is the set of information variables (including a constant) and $\mathbf{F_{t+1}}$ is the set of risk factors. The table also reports the estimate α_p^* obtained by constraining the conditional betas to be constant (i.e., imposing $\kappa_\mathbf{p}' = (\kappa_\mathbf{p0}, \mathbf{0}, \ldots, \mathbf{0})$, where $\kappa_\mathbf{p0}$ is a $K \times 1$ vector of coefficients and $\mathbf{0}$ is a K-vector of zeros), as well as the constant beta estimates. The "difference portfolio" holds the average mutual fund long and the insider portfolio short, with zero net investment. This difference portfolio is formed using either value weights (ω_{it}^h) or ownership weights (ω_{it}^s). See Table I for definitions of $\mathbf{F_{t+1}}$, $\mathbf{Z_t}$, and the value and ownership weights. Asymptotic p-values are in parentheses. Hansen's (1982) goodness-of-fit test statistic, which is asymptotically distributed $\chi^2(12)$, is used to test the following $R = (2KL + 1)$ sample orthogonality conditions under the restriction of constant conditional betas: $E(\mathbf{u1_{p,t+1}}\mathbf{Z_t'}, \mathbf{u2_{p,t+1}}\mathbf{Z_t'}, u3_{p,t+1}) = 0$, with $K = 3$ and $L = 5$.

Mutual Fund/ Portfolio	Mean Monthly Raw Return [Std. dev.]	$\hat{\alpha}_p$	$\hat{\alpha}_p^*$	Constant Beta Estimates *dxmsci*	*rnibor*	*dterm*	Goodness-of-Fit Test
AVEM	0.008	0.011	0.009	0.448	0.230	0.171	10.504
	[0.061]	(0.029)	(0.050)	(0.002)	(0.004)	(0.016)	(0.572)
KAGM	0.006	0.007	0.004	0.424	0.224	0.103	7.025
	[0.067]	(0.195)	(0.425)	(0.004)	(0.005)	(0.121)	(0.856)
KVTM	0.004	0.005	0.004	0.380	0.252	0.069	8.109
	[0.070]	(0.353)	(0.420)	(0.008)	(0.005)	(0.346)	(0.747)
NAKM	0.005	0.008	0.007	0.431	0.217	0.162	6.597
	[0.066]	(0.147)	(0.180)	(0.002)	(0.001)	(0.033)	(0.883)
NOFM	0.005	0.010	0.007	0.419	0.232	0.167	11.979
	[0.068]	(0.073)	(0.171)	(0.003)	(0.005)	(0.024)	(0.447)
NOPM	0.006	0.010	0.007	0.492	0.212	0.191	8.851
	[0.065]	(0.061)	(0.168)	(0.001)	(0.006)	(0.008)	(0.716)
SPIM	0.005	0.007	0.006	0.375	0.232	0.169	9.595
	[0.061]	(0.153)	(0.168)	(0.006)	(0.003)	(0.016)	(0.651)
Avg. mutual fund	0.006	0.007	0.006	0.356	0.193	0.120	8.726
	[0.055]	(0.114)	(0.169)	(0.003)	(0.004)	(0.042)	(0.726)
Difference portfolio, (ω_{it}^h)	0.011	0.008	0.013	−0.043	0.060	−0.112	13.335
	[0.043]	(0.160)	(0.008)	(0.526)	(0.272)	(0.008)	(0.345)
Difference portfolio, (ω_{it}^s)	0.017	0.016	0.020	0.026	0.019	−0.251	15.307
	[0.098]	(0.108)	(0.038)	(0.909)	(0.854)	(0.035)	(0.235)

As reported for insider trades in Table VI, the goodness-of-fit test statistic fails to support the hypothesis that betas are time-varying, which also explains why the alpha estimates in the table are not particularly sensitive to whether or not we assume time-varying betas. Focusing first on the average mutual fund, the hypothesis of zero abnormal performance cannot be rejected at conventional levels of significance using either α_p or α_p^*. The values of these parameters are 0.007 and 0.006 with p-values of 0.114 and 0.169, respectively. Note that these parameter values are indistinguishable from the corresponding alpha-values for the OSE index shown earlier in Table IV (0.007 and 0.005), which are also found to be insignificant. Because the alpha estimates most likely reflect a survivorship bias resulting from our mutual fund sample selection procedure, these estimates are, if anything, overstated. In sum, we conclude that the average mutual fund on the OSE does not exhibit abnormal performance over the sample period. This conclusion is also supported by an examination of the individual mutual fund performance estimates: only one fund of seven shows a Jensen's alpha that is significant at the 5 percent level or better.

Our findings for OSE mutual funds are consistent with the thrust of the evidence on U.S. mutual fund performance whether based on unconditional estimates (e.g., as surveyed by Grinblatt and Titman (1995)) or conditional Jensen's alpha as in the study of 67 open-end mutual funds by Ferson and Schadt (1996). Interestingly, Ferson and Schadt also report that going from an unconditional to a conditional portfolio benchmark approach causes the distribution of Jensen's alpha to shift to the right and to be centered near zero, possibly reflecting a negative bias in unconditional alpha estimates.

Table VIII also provides evidence that the average mutual fund outperforms the portfolio of insider holdings. In the two last rows of the table, although the alpha-estimates based on time-varying betas are both insignificant, the estimate of α_p^* is 0.013 (p-value of 0.008) and 0.020 (p-value of 0.038) when using the value-weighted and ownership-weighted insider portfolios, respectively. Because positive values of alpha means that the average mutual fund outperforms the aggregate insider portfolio, this finding further undermines the view that insiders tend to trade on private, inside information.

Finally, turning to the conditional portfolio weight measure of performance, Table IX reports estimates of Φ_p for each of the seven mutual funds. Due to the data reporting constraints in the sample of mutual funds explained in Section II, this table constrains portfolio weights to be revised three times a year only. That is, we measure the covariance between the reported portfolio weights and the subsequent four-month holding period return residual (thus using nonoverlapping data). The return residuals are obtained by regressing the holding period return from month t to $t+3$ on the instruments $\mathbf{Z_t}$. Thus, the portfolio weights are assumed to be chosen using information available only at the beginning of the four-month period. None of the estimates of Φ_p in Table IX are statistically significant at the 5 per-

Table IX

Conditional Portfolio Weight Measure of Performance Applied to Mutual Funds on the Oslo Stock Exchange, January 1985 to December 1992

This table presents GMM estimates of Φ_p from the following system:

$$\mathbf{u1_{p,t+1}} = \mathbf{r_{p,t+1}} - \Delta'_{\mathbf{p}}\mathbf{Z_t}$$

$$u2_{p,t+1} = \omega'_{\mathbf{pt}}\mathbf{u1_{p,t+1}} - \Phi_p,$$

where $r_{p,t+1}$ is the $N_p \times 1$ vector of portfolio excess returns from t to $t+1$, $\Delta_{\mathbf{p}}$ is the $N_p \times L$ matrix of coefficients from regressing $\mathbf{r_{p,t+1}}$ on the instruments $\mathbf{Z_t}$, including a constant (see Table I), and the parameter Φ_p is the average of the monthly conditional covariances $\omega'_{\mathbf{pt}}\mathbf{u1_{p,t+1}}$. In this table, due to data-reporting restrictions, $\Delta_{\mathbf{p}}$ is estimated by regressing the four-month holding period return (from t to $t+3$) on the instruments $\mathbf{Z_t}$. The GMM estimation imposes the restriction that $E(\mathbf{u1_{p,t+1}}\mathbf{Z'_t}, u2_{p,t+1}\mathbf{Z_t}) = 0$. The choice of a four-month holding period reflects the fact that, in our data, the mutual fund portfolio weights are updated three times a year. In the above estimation, the portfolio weights for each four-month holding period are assumed to be chosen using information available only at the beginning of the period. A security with missing price data is given zero weight in the month that it is missing. Asymptotic p-values are in parentheses.

Covariance Measure	Mutual Fund						
	AVEM	KAGM	KVTM	NAKM	NOFM	NOPM	SPIM
$\hat{\Phi}_p$	0.000 (0.994)	−0.001 (0.973)	−0.002 (0.895)	−0.001 (0.949)	0.000 (0.977)	−1.086 (0.966)	0.000 (0.991)

cent level.[13] In sum, jointly with Table VI, we find no evidence, using the conditional covariance measure, that either the aggregate insider portfolio or the managed mutual funds earn superior returns.

V. Conclusion

This paper evaluates the performance of the population of insider holdings and trades on the Oslo Stock Exchange during a period with relatively lax insider regulations and enforcement. The evaluation proceeds by forming portfolios of monthly aggregate insider holdings, which reflect the insiders' actual holding periods in their respective stocks, and then subjecting these portfolios to modern techniques of performance measurement. Moreover, we compare the performance estimates for the aggregate insider portfolios to the performance of managed mutual fund portfolios on the OSE over the same time period.

[13] This conclusion is broadly consistent with the results in Grinblatt and Titman (1993) who study quarterly portfolio holdings of 155 U.S. mutual funds from 1975 to 1984.

Our empirical methodology incorporates and extends recent developments in the literature on mutual funds and our study is the first to apply these techniques to insider trades. Thus, we employ the conditional portfolio benchmark approach of Ferson and Schadt (1996) to produce estimates of Jensen's alpha in a world with time-varying expected excess returns. Moreover, we extend the portfolio weight approach of Cornell (1979) and Grinblatt and Titman (1993) and estimate the conditional covariance between monthly insider holdings and subsequent portfolio returns. For comparison purposes, we also perform a conditional version of the traditional event-study technique that has produced much of the important stylized facts often referred to in the public debate on insider trading regulations.

Overall, the performance analysis rejects the hypothesis of positive abnormal performance by insiders. This conclusion appears robust to the weighting scheme and to a variety of trade characteristics, including the size and direction of the trade. Portfolio weights based on the level of insider holdings (measured using either dollar value invested or by the fraction of the firms' shares held), or sorted based on the change in insider holdings (which excludes periods of nontrading), produce statistically insignificant or negative abnormal performance.

At first sight, this conclusion appears to contradict the findings of several empirical studies on insider trades in other markets, such as those by Seyhun (1986) on U.S. firms, Fowler and Rorke (1984) on Canadian firms, and Pope et al. (1990) in the United Kingdom. Using classical event study techniques, these studies generally find significant evidence of insiders purchases before abnormal price increases and sales before abnormal price decreases. In fact, when we apply this classical technique to our data, we find some evidence of abnormal returns over a four-month period following insider trades, primarily from sale transactions. However, it appears that this abnormal return is driven by the methodology itself: The abnormal return largely disappears in a conditional multifactor setting and when the portfolio weights are constructed to more closely mimic relative trade size. Finally, our more general performance measures also allow portfolio weights to vary through time reflecting actual insider holding periods, which appears to further eliminate evidence of abnormal performance produced by the classical event-study approach.

Relative to the administratively centralized asset allocation decisions of mutual fund managers, the performance of the insider portfolio "suffers" from the decentralized nature of individual insiders' trading decisions. Moreover, insiders enjoying corporate control benefits from their ownership positions may optimally decide not to sell even in situations where publicly available information used by mutual fund managers dictates that such sales will increase expected returns. Thus, for insiders to receive a higher average risk-adjusted return than mutual funds, they must trade on inside information, making the comparison with mutual fund performance particularly interesting. Our results indicate that insiders on average do not outperform the average mutual fund in our sample.

Given the extensive sensitivity analysis performed throughout this paper, our finding of statistically insignificant abnormal performance of the aggregate insider portfolio appears robust. Perhaps insiders, in a market like the OSE, only rarely possess inside information, or perhaps the value of maintaining corporate control benefits tends to offset the value of trading on such information. A further discrimination between these two alternative explanations for our finding is left for future research.

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