# ESTIMATING THE RETURNS TO INSIDER TRADING: A PERFORMANCE-EVALUATION PERSPECTIVE

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*Abstract*——This paper uses performance-evaluation methodology to estimate the returns earned by insiders when they trade their company's stock. Our methods are designed to estimate the returns earned by insiders themselves and thereby differ from the previous insider-trading literature, which focuses on the informativeness of insider trades for other investors. We find that insider purchases earn abnormal returns of more than 6% per year, and insider sales do not earn significant abnormal returns. We compute that the expected costs of insider trading to noninsiders are about 10 cents for a $10,000 transaction.

## I. Introduction

What are the returns to insider trading? This question has scientific implications for the study of market efficiency, and public policy implications for the regulation of insider trading. Unfortunately, data limitations prevent a complete answer, as the holding periods of insider transactions can only be imperfectly inferred from the regulatory filings. These limitations have led researchers to largely ignore the returns question in favor of studies that focus on a different aspect of insider trading—namely, the ability of outside investors to profit by following "intensive" insider trading. In this paper, we take advantage of legal restrictions on the holding periods of profitable insider trades—Rule 16b of the Securities Exchange Act of 1934, or the "short-swing" rule—to estimate a proxy for the returns to insider trading itself.

By law, corporate insiders must file monthly SEC reports about their trades in their company's stock, and these reports are quickly made public.[1] These data on insider trading have inspired a large academic literature that studies the cross-sectional variation of future stock returns as a function of past insider-trading activity. Representative articles include Lorie and Niederhoffer (1968), Jaffe (1974), Seyhun (1986, 1998), Rozeff and Zaman (1988), Lin and Howe (1990), and Lakonishok and Lee (2001).[2] This literature focuses on the abnormal returns to firms in relation to the intensity of insiders' purchases and sales over well-defined periods. For example, a stock may be labeled an insider buy for a month if at least three insiders bought the stock and no insiders sold it. Alternatively, the intensity definition may rely on the net number of shares purchased and sold by insiders during the month, with an insider buy being a company purchased in net by insiders. We refer to such rules as *intensive-trading* criteria. These studies use a variety of intensive-trading criteria for many different samples, and are nearly unanimous in concluding that stocks that are intensively bought tend to outperform relevant benchmarks over a subsequent period, and that those that are intensively sold tend to underperform. They provide mixed evidence on whether other investors can profit, after transaction costs, by using this information. Seyhun (1998) summarizes this evidence and concludes that several different trading rules lead to profits.

Intensive-trading criteria vary, but they all share two common features: (1) analysis of abnormal returns averages across *firms* (not trades) after firms have been classified as purchases and sales, and (2) the classification of firms into purchases and sales uses some filter rule defined over monthly (or longer) time periods, and firms are only reclassified after each period. Such criteria are logical filter rules when assessing the informativeness of insider trading for future returns, and for providing investors with implementable buy and sell signals for individual stocks. But what if we want a proxy for what insiders earn on their own trades? For that purpose, intensive-trading criteria have several drawbacks. First, the use of individual stocks as the main unit of analysis makes it impossible to determine a value-weighted return to all *trades;* the stocks with intensive buying or selling activity may constitute a small or a large part of overall insider trading. Second, the requirement that intensity be defined over some interval means that stocks are only classified after these intervals end. Therefore, the returns on the days immediately following most trades are excluded from the analysis. Third, the need to choose a specific intensity rule can result in data-snooping biases. Attempts to overcome these challenges by applying event-study methods to daily returns for all trades (Pascutti, 1996) face statistical difficulties due to cross-sectional correlation across trades and biases in computing long-run abnormal returns.[3]

We overcome these difficulties by employing performance-evaluation methods on value-weighted portfolios. We imagine that all insider purchases are placed in a portfolio beginning on the day after their execution and are held for exactly 6 months. This *purchase portfolio* is like a shadow mutual fund managed by the combination of all insiders. Since the holdings in this portfolio are weighted in proportion to the values of the underlying insider trades, the

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[1] Section II discusses the definition of a corporate insider, and the regulation and reporting requirements for their trades.

[2] A related literature studies insiders' ability to forecast the time series of aggregate stock returns, a topic we do not discuss in this paper. See Seyhun (1988, 1992, 1998) and Lakonishok and Lee (2001).

[3] See Barber and Lyon (1997), Barber, Lyon, and Tsai (1999), and Kothari and Warner (1997).

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returns on the portfolio will proxy for the value-weighted returns earned by all insider purchases over six months. Similarly, we can imagine a *sale portfolio* composed of all shares sold by insiders, with those shares held in the portfolio for exactly 6 months.

An important advantage of this portfolio-based approach is that it enables us to use performance-evaluation techniques to adjust for the style of insider trading—that is, to take account of implicit or explicit size, value, and momentum strategies used by insiders. Another advantage is that it allows portfolios to be decomposed by time horizon, firm characteristics, and trading volume. By constructing subportfolios, point estimates and standard errors can be obtained for the abnormal returns to value-weighted insider trades conditional on each of these elements. The 6 month holding period, though arbitrary, corresponds to the minimum time that an insider must hold a stock while still retaining profits from an offsetting transaction. Rule 16b of the SEA, the short-swing rule, states that "profits made by insiders from transactions involving equity securities of publicly held companies, when a purchase and a sale are made less than 6 months apart, must be disgorged and paid over to the issuer."[4] Thus, any profits realized for holding periods less than 6 months would have to be returned to the company.[5] In some sense, then, the returns to our constructed portfolios can be viewed as maximum *realizable* returns from the reported transactions.

Ideally, of course, we would prefer to know the true holding periods. There are several limitations that make such an analysis impossible for U.S. data. Although insider holdings are available from proxy statements and other filings, many of these holdings have come from stock grants, option exercises, and stock amassed before insider status was achieved. Thus, we cannot determine the date that most of these shares were acquired. Since insiders are net sellers of shares, and the date of acquisition for most shares is unknown, the true holding periods cannot be calculated for most transactions. Due to these data limitations, it is not possible to compute actual returns to insider trading. We rely instead on the proxy returns from our constructed purchase and sale portfolios.

From a scientific perspective, analysis of the purchase and sale portfolios provides a new perspective on the strong form of market efficiency (Fama, 1970): if either portfolio earns abnormal returns, that provides evidence against strong-form efficiency for the corresponding asset-pricing model. Since our methods include all returns from the day of the transaction and do not require a predefined intensive-trading rule, they provide a sharper test of this hypothesis than is found in previous insider-trading papers. It is important to stress that we do not claim that the results of this previous literature are invalid, but rather that they are designed to answer different questions. Intensive-trading rules are the ideal tools for analyzing the informativeness of insider trading for future returns and for providing outside investors with filter rules to use this information. Throughout the paper, we distinguish between intensive-trading studies that analyze the informativeness of insider trading, and our portfolio methods that analyze a proxy for the returns earned by insiders themselves.

Beyond the scientific benefits it brings, our analysis also addresses policy concerns. If abnormal returns to the purchase and sale portfolios are large, that suggests that insiders are earning profits from their trades. If so, then what are the welfare implications? Even accepting the premise, there is a range of opinion.[6] Some laissez-faire observers believe that insider trading should be legal, and that profits from it should be part of corporate compensation. At the opposite extreme, financial puritans would object to the insiders' profits as unjust enrichment, even if there were no consequences for market (or corporate) performance.[7]

Lying in between is the position of American regulators, whose principal concern is to assure that the playing field is level. For them, abnormal returns to the purchase or sale portfolios would be a symptom of markets that are unfair to the outside investor, who would then be trading at an informational disadvantage. Such a disadvantage would undermine rational outsiders' confidence in such markets, diminish their willingness to trade, and thus reduce liquidity and efficiency within financial markets. In practice, these effects will depend on perceptions of market fairness, not merely reality. It is virtually impossible for outsiders to assess their potential disadvantage in such markets, absent the detailed analysis developed below.

Two other studies employ variants of the portfolio approach used in our paper. Finnerty (1976) uses the CAPM to evaluate the equally weighted returns to all insider trades in NYSE stocks from 1969 to 1972. He finds that buys overperform and sales underperform their CAPM benchmarks. Though equal weighting is reasonable for this study, which is motivated solely as a test of the strong form of market efficiency, it is clearly inappropriate as a proxy for value-weighted insider returns. Eckbo and Smith (1998) use performance-evaluation methods on monthly data for the complete sample of value-weighted insider holdings in Norway from 1985 to 1992. They find that Norwegian insiders do not earn abnormal returns.

Overall, we find that the purchase portfolio earns abnormal returns but the sale portfolio does not. In raw returns, the purchase portfolio outperforms the market by 11.2% per

[4] *Understanding Securities Law,* Soderquist (1998).

[5] Agrawal and Jaffe (1995) find that this rule deters purchases of stock by insiders in merger-target firms. We are unaware of any other study that explicitly relies on the 6 month minimum short-swing horizon.

[6] See Bainbridge (2000) for a survey of this debate.

[7] Their disapproval would not vanish even if it could be demonstrated that insider trading brought significant net benefits, say because it brought stock prices more firmly into alignment with appropriate values—as historical Puritans (according to Macaulay) objected to bear baiting, not because it gave pain to the bear, but because it gave pleasure to the spectators.

year. Using several performance-evaluation methods, we find that about one-third of this overperformance can be explained by insiders' propensity to buy small stocks, "value" stocks, and those with higher market β's. Across the different methods, the remaining abnormal performance ranges between 52 and 68 basis points per month. About one-quarter of these abnormal returns accrue within the first five days after the trade, and one-half accrue within the first month.

Despite the economically significant abnormal returns to the purchase portfolio, we find that counterparties (outsiders) have little to fear from these reported transactions, because insider trades make up but a tiny portion of the market. We calculate that the expected cost to outsiders due to the purchases of insiders is about 0.10 basis points over the subsequent six months. This translates into 10 cents for a $10,000 transaction.

In raw returns, the sale portfolio performs about the same as the value-weighted market. Consistent with previous studies, we find that insiders tend to sell growth stocks that have performed well in the recent past. When we use performance-evaluation methods to control for this tendency, we find abnormal returns that are both economically and statistically insignificant. This result demonstrates that the informativeness of intensive trading is not necessarily a good proxy for value-weighted insider returns: many studies find that intensive insider selling forecasts negative abnormal returns.

Following our analysis of the purchase and sale portfolios, we look at the portfolios decomposed along several dimensions: volume of the trade, size of the firm, insider's position in the firm, and whether the trade is executed directly for an insider or indirectly for another party. These categories have been studied previously using intensive-trading criteria or event-study methods. We find that several of the results from intensive-trading studies do not carry over to the analysis of insider returns. For example, purchases in small firms do not earn significantly higher returns than do purchases in large firms, and the purchases of top executives do not earn significantly higher abnormal returns than do those of other insiders.

The paper is organized as follows. Section II discusses the data and provides summary statistics. Section III describes the three performance-evaluation methods we employ. Section IV gives the performance-evaluation results for the main insider-purchase and insider-sale portfolios. Section V analyzes decompositions of the purchase and sale portfolios by trade volume, firm size, book-to-market ratio, and the insider's relationship to the firm. The conclusion summarizes and interprets our results.

## II. Data and Summary Statistics

The Securities and Exchange Act of 1934 (SEA) prohibits agents from trading securities while in possession of material inside information. "Material insider information" can be loosely defined as private information that a reasonable investor would consider important in the decision to buy or sell a corporation's security.[8] The enforcement of the SEA was substantially strengthened by the Insider Trading Sanctions Act of 1984 and the Insider Trading and Securities Fraud Enforcement Act of 1988. In response, many companies instituted their own restrictions on insider trading, as safe-harbor measures and to avoid any appearance of illegality.[9]

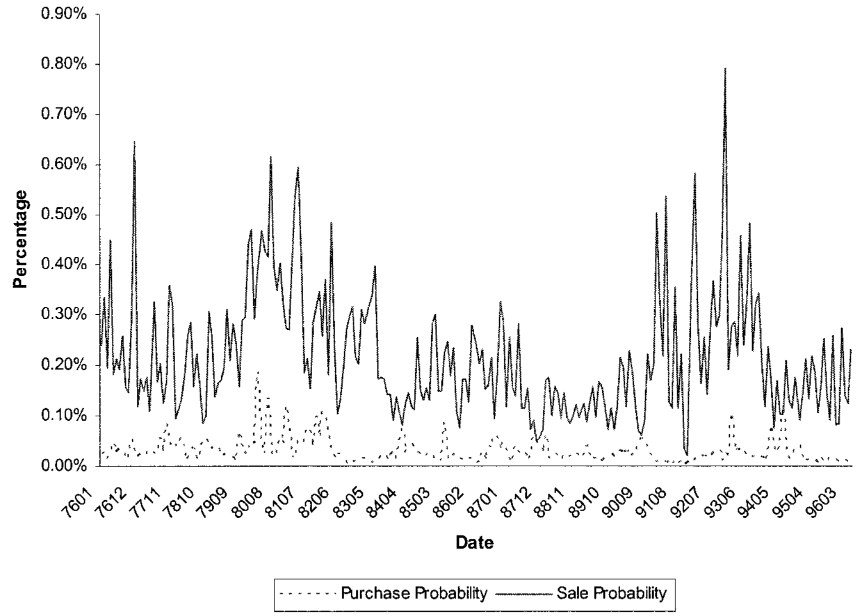
To facilitate enforcement of the regulations, section 16a of the SEA requires that open-market trades by corporate insiders be reported to the Securities and Exchange Commission (SEC) within 10 days after the end of month in which they took place. For the purposes of this reporting requirement, "corporate insiders" include officers with decision-making authority over the operations of the company, all members of the board of directors, and beneficial owners of more than 10% of the company's stock. These reports, filed on the SEC's Form 4, are the source of data for almost all of the empirical studies of insider trading.[10] Our data are drawn from these Form 4 filings for the period from January 1, 1975 to May 31, 1996. These filings contain information about each transaction and about the insider's relationship to the firm. (See appendix A for more information about Form 4).

Our analysis focuses on open-market purchases and sales by officers and directors. We exclude options exercises, private transactions, and all transactions by beneficial owners. The resulting database contains 558,229 transactions over approximately 21 years, of which 208,055 are purchases and 350,174 are sales.[11] Sales outnumber purchases particularly in later years when option and stock awards began to become a significant part of officers' and directors' compensation; such awards do not show up as purchases, but they do show up as sales when the positions are liquidated. The typical sale is substantially larger than the typical purchase, with average dollar values of $123,100 per sale as compared with $30,700 per purchase.

On a value-weighted basis, what percentage of all trades are made by insiders? This percentage is straightforward to calculate as the dollar volume of insider purchases and sales divided by the dollar volume of all trades. We calculate these percentages separately each month for both purchases and sales, and we plot the time series of these percentages in figure 1. Over the whole sample period, the average monthly ratio of value-weighted insider sales to all trades is 0.22%. Thus, an outsider making a purchase would expect 0.22 cents per dollar to have an insider as counterparty. The average monthly ratio of insider purchases to all trades is

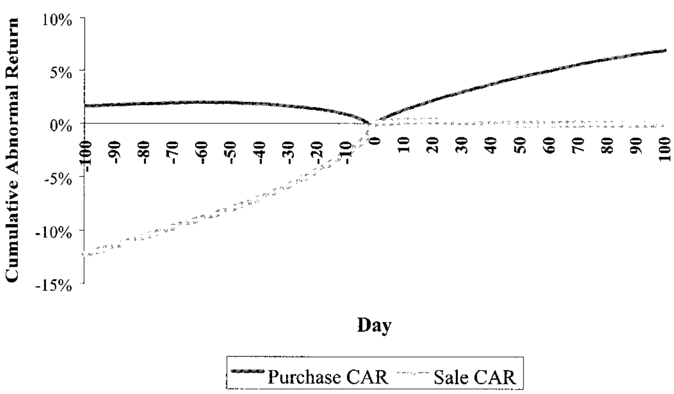
[8] For a detailed discussion of the SEA, see Bainbridge (2000).
[9] Jeng (1998).
[10] Exceptions are Meulbroek (1992), Cornell and Sirri (1992), Chakravarty and McConnell (1997, 1999), and Gompers and Lerner (1998).
[11] We performed several steps to purge the data of coding errors. See appendix A.

FIGURE 1.—PERCENTAGE OF MARKET VOLUME TRADED BY INSIDERS




This figure plots insiders' purchases and sales as a percentage of market volume for each month of the sample period. The percentage is calculated as the total value in all securities of insider purchases (sales) for that month divided by the total value of all monthly trading on NYSE, AMEX, and Nasdaq. The average percentages across the whole sample are 0.03% for purchases and 0.22% for sales.

FIGURE 2.—CUMULATIVE ABNORMAL RETURNS MEASURED FROM THE DATE OF INSIDER TRANSACTIONS




This figure plots the average cumulative abnormal return (CAR) measured from the date of insider purchase and sale transactions. Daily abnormal returns are defined here as a stock's return minus the value-weighted market return. These daily abnormal returns are calculated for the day of the transaction (day 0) and for each of the 100 days before and after the transaction. The CAR for day $-t$ is the sum of daily abnormal returns beginning on day $-t$ and ending on day 0. The CAR for day $t$ is the sum of the daily abnormal returns beginning on day 0 and ending on day $t$. This procedure yields a time series of CARs for each insider purchase and sale; these CARs are averaged across all purchases and sales to produce the figure. The sample is for transactions from January 1, 1975 to May 31, 1996.

0.03%. Thus, outsiders making sales would expect only 0.03 cents per dollar to be with insiders.

Many studies of insider trading show that insiders sell stocks after they rise and buy them after they fall.[12] We also see this in our sample, as figure 2 makes vivid. We calculated an abnormal return for every trade on every day, where abnormal returns are defined as the stock's return minus the return on the value-weighted market (NYSE, AMEX, or Nasdaq). Cumulative abnormal returns (CARs) are measured relative to the trading day by adding the daily abnormal returns for all intervening days. These CARs are then averaged across all firms and graphed in the figure. Thus, this analysis equally weights all trades beginning on the day of their execution.

Figure 2 shows that, on average, an insider sale is preceded by a positive CAR of about 12% over the preceding 100 days, but there is no noticeable CAR after the sale. Purchases are preceded by a negative CAR of about 2% over the 100 days prior to the trade date, and are followed by a positive CAR of about 6% over the subsequent 100 days.

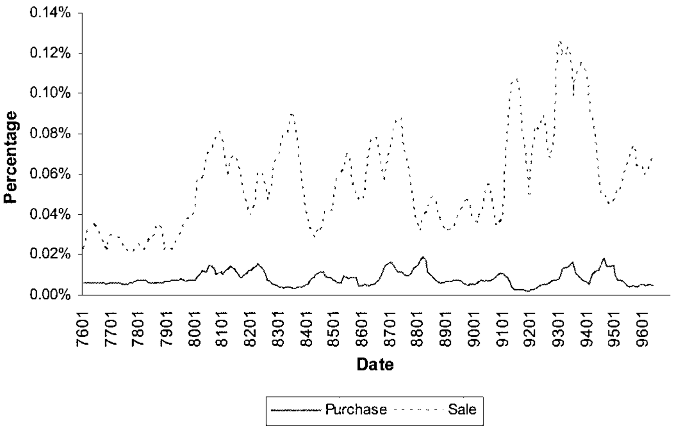
The average CARs graphed in figure 2 provide only a crude measure of the abnormal returns to insider trades. Aside from the obvious difficulties of using the value-weighted market as the expected-return proxy for all stocks, there are also statistical problems due to biases in the computation of CARs and the cross-sectional dependence of the abnormal returns among transactions of the same firm and across firms.[13] We sidestep these problems by constructing *purchase* and *sale* portfolios and analyzing their returns with performance-evaluation methods. To construct the purchase portfolio, we buy all insider purchases at the closing prices on the day of the actual trades.[14] We then hold these shares in the portfolio for 6 months. Thus, the purchase

[12] Seyhun (1986, 1998), Lakonishok and Lee (2001), Rozeff and Zaman (1998).

[13] See Barber and Lyon (1997), Kothari and Warner (1997), and Barber, Lyon, and Tsai (1999).

[14] We use closing prices on the day of the trade rather than the actual transaction prices of the insider transaction because of concerns about errors in the reporting of transaction prices. See appendix A for a complete discussion of this issue.

FIGURE 3.—INSIDER PURCHASE AND SALE PORTFOLIOS AS A PERCENTAGE OF TOTAL MARKET CAPITALIZATION




This figure shows the percentage of the market held in insider purchase and sale portfolios. The purchase (sale) portfolio includes all shares purchased (sold) by insiders over the previous six months. On each day, we calculate the percentage of the total market value (NYSE/AMEX/Nasdaq) held in each of these portfolios. Monthly percentages are expressed as the mean of the daily percentages from that month. These monthly percentages are then plotted in the figure. For the sample period of January 1, 1976 to May 31, 1996, the averages of these monthly percentages are 0.01% for purchases and 0.06% for sales.

portfolio includes all shares purchased by insiders over the previous 6 months. Similarly, the sale portfolio contains all shares sold by insiders over the previous 6 months.

Figure 3 plots the total market value of the purchase and sale portfolios as fractions of the overall market. We begin the analysis of these portfolios on January 1, 1976.[15] As would be expected, the sale portfolio is always larger than the purchase portfolio. With all sales held for 6 months after the insider transaction, the sale portfolio averages about 0.06% of the market. It is larger in recent years and reaches a peak of 0.13% of the market in 1993. The size of the purchase portfolio averages about 0.01% of the market and does not display any obvious pattern over time.

The purchase and sale portfolios are likely to differ along many dimensions. First, we would expect to observe more insider sales than purchases, if only to meet diversification and liquidity objectives. High-ranking corporate officers typically have substantial human capital invested in their firms and often have large holdings of corporate stock and options relative to their wealth.[16] In addition, much executive compensation comes in the form of stock and options, and these additions to insiders' personal portfolios will not show up in our database. In fact, a value-weighted plot of option exercises (not shown here) shows a striking similarity to the plot of sales given in figure 1; such similarity would be expected if many sales are executed in conjunction with option exercises. Overall, we would expect that insider purchases are more likely than sales to be information-driven.

Second, the purchase and sale portfolios differ from each other and from the overall market in their stock composition; insiders tend to trade in stocks that are smaller in market capitalization than the average stock, this pattern being more pronounced for purchases.[17] As an illustration, we compute the fraction of the purchase and sale portfolios made up by the largest and smallest stocks, and we compare these fractions with analogous fractions for the whole market. These fractions are computed for July 1 of each year and then averaged across all years from 1976 to 1996. We define the *largest* stocks as those with market capitalizations above the cutoff for the largest third of the stocks on the NYSE. Analogously, the *smallest* stocks are those with market capitalizations below the cutoff for the smallest third. Using these cutoffs, we classify all stocks traded on NYSE, AMEX, and Nasdaq. Naturally, the largest stocks comprise a far larger component of the value of the overall market (83.1%) than do the smallest stocks (5.5%). In contrast, the sale portfolio derives only 35.9% of its value from the largest stocks and 32.5% from the smallest stocks. The purchase portfolio has an even more extreme tilt toward small stocks, with only 22.9% of its value from the largest stocks and 36.5% from the smallest stocks.

Rozeff and Zaman (1998) and Lakonishok and Lee (2001) show that insiders tend to buy value stocks and sell growth stocks, as defined by several different measures of value and growth. This pattern also emerges in our purchase and sale portfolios, and can be illustrated with a portfolio decomposition similar to the one performed for size. On July 1 of each year, we calculate a book-to-market (BM) ratio for all stocks using their book value for the most recent fiscal year (from COMPUSTAT) divided by market value as of the previous December 31. We then rank all NYSE stocks by their BM ratios and find the cutoffs for the highest third (value) and the lowest third (growth), and we use these cutoffs to classify all stocks. Next, we calculate the fractions of the purchase portfolio, sale portfolio, and overall market that fall into the value and growth categories. These fractions are computed once per year and then averaged across all years from 1976 to 1996. Using these definitions, the overall market consists of 50.2% growth stocks and 20.3% value stocks (and 29.5% in between). Relative to the market, the sale portfolio exhibits a slight tilt toward growth stocks, with 54.1% growth and 18.1% value. The purchase portfolio exhibits a strong value tilt, with an average of 34.3% growth and 29.8% value.

What are the returns to the purchase and sale portfolios? Consistent with the results of figure 2, the purchase portfolio outperforms the market, whereas the sale portfolio earns returns very close to the market. The annualized returns are 26.3% for the purchase portfolio, 15.9% for the sale portfolio, and 15.6% for the market.[18] Note that an insider

[15] The portfolios have incomplete 6 month histories before July 1, 1975, so that prior dates would not be comparable to subsequent ones. We begin on the following January 1 so that we have only complete years in the analysis.

[16] Hall and Liebman (1998).

[17] Seyhun (1986); Rozeff and Zaman (1988).

[18] This calculation ignores transaction costs, a policy that we follow throughout the paper and one that is consistent with our purposes. One

advantage should yield overperformance for the purchase portfolio and underperformance for the sale portfolio. Of course, simple comparisons of portfolio returns with the market tell only part of the story. To learn more, we need to use performance-evaluation methods and calculate abnormal returns. We turn to this task in the next section.

## III. Performance Evaluation: Methods

In the section, we describe the performance-evaluation methods that we use to analyze insider's returns. Since there is no consensus on the right model of expected returns, we employ three methods that have proved useful in similar studies. Our first method of performance evaluation is the standard CAPM of Sharpe (1964) and Lintner (1965).

METHOD 1: CAPM:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \, RMRF_t + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the return on insider portfolio $i$ in month $t$, $R_{f,t}$ is the risk-free return in month $t$, and $RMRF_t$ is the month-$t$ value-weighted market return minus the risk-free rate. Here, $\alpha_i$ can be interpreted as the abnormal return to portfolio $i$. Although research over the past 20 years has produced significant evidence against this unconditional version of the CAPM, it is still used for performance evaluation, by both academics and practitioners.[19] Thus, it provides a good starting point for our analysis.

METHOD 2: FOUR-FACTOR MODEL: One problem for the unconditional CAPM is that it cannot explain differences in returns for portfolios sorted by standard characteristics such as size, past returns (momentum), or measures of value such as the price-to-earnings, cash-flow-to-price, and BM ratios.[20] Since there is evidence that the purchase and sale portfolios differ from the market with respect to size, momentum, and value, it is important that we adjust for these strategies in our analysis. The four-factor model of Carhart (1997) is ideally suited for this purpose and has proved useful in several recent studies of performance evaluation.[21] The model is estimated by

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,1} \, RMRF_t + \beta_{i,2} \, SMB_t + \beta_{i,3} \, HML_t + \beta_{i,4} \, PR1_t + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$, $R_{f,t}$, and $RMRF_t$ are defined as in equation (1). The variables $SMB_t$ (small minus big), $HML_t$ (high minus low), and $PR1_t$ (previous one-year return) are the month-$t$ returns to zero-investment factor-mimicking portfolios designed to capture size, BM, and momentum effects, respectively.[22] Although there is an ongoing debate about whether these factors are proxies for risk, we take no position on this issue and simply view the four-factor model as a method of performance attribution. Thus, we interpret the estimated $\alpha$'s as abnormal returns in excess of what could have been achieved by passive zero-cost investments in the factors.

METHOD 3: CHARACTERISTIC-SELECTIVITY MEASURE: Our third measure of performance is the *characteristic-selectivity* (CS) measure developed by Daniel et al. (1997). This method matches each insider transaction with a portfolio of similar stocks, and then calculates an excess return relative to this portfolio on each day. This approach takes advantage of the transactions nature of the data, which substantially increases the precision of abnormal-return estimates under some circumstances.[23] Though the procedure is conceptually straightforward, it is notationally cumbersome. We describe the basic idea here and cover the details in appendix B.

To obtain the CS measure, we begin by constructing 125 bins through independent $5 \times 5 \times 5$ sorts on size, BM ratio, and momentum quintiles. NYSE breakpoints are used for size and BM ratio, and combined NYSE-AMEX-Nasdaq breakpoints are used for momentum, with all NYSE, AMEX, and Nasdaq stocks placed in quintiles on the basis of these breakpoints. Size and BM sorts are performed once a year (on July 1); momentum sorts are performed at the beginning of every month. Therefore, stocks can change bins every month. The three characteristics serve an analogous role to the $SMB$, $HML$, and $PR1$ factors in the four-factor model. In the CS approach, all stocks with the necessary data are allocated to a bin, which we call its *matching bin.*[24] Next, we calculate a daily value-weighted return for each bin. Then, for each of our insider portfolios, the monthly measure of abnormal returns is calculated as the return on a zero-investment portfolio that is long the insider portfolio and short a portfolio constructed using equivalent weights in the matching bins.

We write $R_{i,t}$ for the return to insider portfolio $i$ in month $t$, and $Bin_{i,t}$ for the return to the matching bins of insider portfolio $i$ in month $t$. Then, the abnormal return to portfolio $i$ for that month, $CS_{i,t}$, is equal to the difference between

could easily approximate the annual transaction costs for these portfolios by multiplying portfolio turnover (200%, by construction) by an estimate of round-trip transaction costs.

[19] Examples of the CAPM's continuing role in performance evaluation are Malkiel (1995), Morningstar (1996), and Shirk, Cuenca, and Carlson (1997).

[20] See Basu (1977) (P/E ratio), Banz (1981) (size), Fama and French (1993) (size and BM ratio), Lakonishok, Shleifer and Vishny (1994) (several value measures), and Jegadeesh and Titman (1993) (momentum).

[21] See Carhart (1997), Chevalier and Ellison (1999), Daniel et al. (1997), and Metrick (1999).

[22] This model extends the Fama-French (1993) three-factor model with the addition of a momentum factor. For details on the construction of the factors, see Fama and French (1993) and Carhart (1997). We are grateful to Mark Carhart for providing the factor returns.

[23] See Metrick (1999).

[24] Since some stocks must be excluded from this analysis because of failure to match, the returns on the purchase and sale portfolios will be slightly different here than for the factor models. Appendix B, which discusses these issues, shows that any differences are small.

TABLE 1.—PERFORMANCE-EVALUATION RESULTS FOR PURCHASE AND SALE PORTFOLIOS

| | Purchase Portfolio | | | Sale Portfolio | | |
|---|---|---|---|---|---|---|
| | CAPM | 4-Factor | CS Measure | CAPM | 4-Factor | CS Measure |
| $\alpha$ | 0.0068** (0.0017) | 0.0052** (0.0013) | | −0.0017 (0.0014) | −0.0005 (0.0010) | |
| *RMRF* | 1.1471** (0.0394) | 1.0965** (0.0320) | | 1.3152** (0.0331) | 1.1273** (0.0251) | |
| *SMB* | | 0.7395** (0.0490) | | | 0.5473** (0.0384) | |
| *HML* | | 0.1773** (0.0531) | | | −0.4089** (0.0416) | |
| *PR1* | | −0.0607 (0.0448) | | | 0.0529 (0.0351) | |
| *CS* | | | 0.0053** (0.0014) | | | −0.0002 (0.0010) |
| $R^2$ | 0.7723 | 0.8861 | | 0.8635 | 0.9406 | |

This table presents the performance-evaluation results for the purchase portfolio. The purchase portfolio includes all shares purchased by insiders over the previous 6 months. Column 2 gives the results for the CAPM [equation (1)]. Column 3 gives the results for the four-factor model [equation (2)]. Column 4 gives the results for the CS measure [equation (3)]. For the factor models, $\alpha$ is the regression intercept, and the next four rows give coefficients and standard errors (in parentheses) for the independent variables: *RMRF, SMB, HML*, and *PR1*. These independent variables are the returns to zero-investment portfolios designed to capture market, size, book-to-market ratio, and momentum effects, respectively. [Consult Fama and French (1993) and Carhart (1997) on the construction of these factors.] The symbols * and ** indicate two-tail significance at the 5% and 1% levels, respectively. The bottom row of the table provides the $R^2$ for the factor regressions. The sample is from January 1, 1976 to May 31, 1996.

these two returns: $CS_{i,t} = R_{i,t} - Bin_{i,t}$. For the 252 months of the sample period, the overall performance measure, $CS_i$ is written as

$$CS_i = \frac{\sum_{\text{Jan. 76}}^{\text{Dec. 96}} CS_{i,t}}{252}. \tag{3}$$

In this setup, $CS_i$ is comparable to $\alpha_i$ from the factor models. Its statistical significance can be assessed by using the time-series standard error of $CS_{i,t}$.

The next two sections show that these three methods provide very similar results for the abnormal returns of insiders. There are additional methods, of course, that could be used to analyze returns, but no single analysis could employ all of them.[25] We have no reason to believe that our results would be qualitatively different using other methods.

## IV. Performance Evaluations: Results

### A. *Performance Evaluation of the Purchase and Sale Portfolios*

This section applies each of the three performance-evaluation methods to the purchase and sale portfolios. In discussing the results, we use "performance measure" and "abnormal returns" as synonyms. Table 1 summarizes the results. Under the CAPM, the purchase portfolio has a significant $\alpha$ of 68 basis points per month.[26] The CAPM $\beta$ is 1.15 and is significantly greater than 1. As we discussed in section II, insiders tend to purchase small stocks, value stocks, and those with low momentum. This strategy is also evident in the factor loadings (or $\beta$'s) from the four-factor model, given in the third column of the table: positive and significant loadings on *SMB* and *HML*, and a negative but insignificant loading on *PR1*. For the whole sample period, the average returns are positive for all of these factors, so whereas the positive loadings on *SMB* and *HML* explain some of the abnormal performance observed in the CAPM, the negative loading on *PR1* works in the opposite direction. Together, these factor loadings account for about one-quarter of the abnormal return from the CAPM, and the four-factor model $\alpha$ is a significant 52 basis points. Notice that the adjusted $R^2$ for the four-factor model is higher than for the CAPM (0.89 versus 0.77), and this added explanatory power results in a relatively large difference in the standard errors of the respective $\alpha$ estimates (17 versus 13 basis points).

The CS measure for the purchase portfolio is similar to those for the CAPM and the four-factor model, with a significant estimate of 53 basis points. Since the CS measure is computed using a completely different method than are the $\alpha$'s in the factor models, the similarity in results is reassuring. Taken together, the evidence from the table shows that insiders earn economically large abnormal returns from their purchases, with point estimates ranging between 52 and 68 basis points per month.

The results for the sales portfolio appear in the right-hand panel of table 1. Here, all performance measures are economically small and statistically insignificant. The CAPM $\alpha$ is −17 basis points with a standard error of 14 basis points.

[25] For example, we do not employ any conditional factor models such as in Eckbo and Smith's (1998) study of insider trading in Norway. We believe that the CS approach addresses similar concerns to those of conditional models, with the added advantage that it exploits the transactions nature of the data.

[26] Unless otherwise noted, "significant" refers to statistical significance at the 5% level.

The CAPM β of 1.32 is significantly greater than even the CAPM β from the purchase portfolio.

For the four-factor model, the loadings for the sale portfolio are different from those found for the purchase portfolio, these differences being consistent with our analysis in section II and with the results of Rozeff and Zaman (1998). The loading on *HML* is negative and significant, suggesting a tilt toward growth stocks. The loading on *SMB*, though positive, is significantly lower than for the purchase portfolio. Interestingly, the loading on *PR1*, though positive, is economically small and statistically insignificant. Thus, even though insiders tend to sell stocks that have recently increased in price, these stocks do not subsequently perform like other high-momentum stocks. With these loadings, the four-factor model yields a negative but insignificant α of −6 basis points per month. For the CS measure, the point estimate is an insignificant −2 basis points per month. In sum, there is no significant evidence that insiders earn abnormal returns in the sale portfolio.

Overall, these results show that outsiders have little to fear from insiders, at least those who report their trades. Consider an outsider contemplating the sale of a stock. It is possible that this sale will be made to an insider. In table 1, the average monthly abnormal return for the purchase portfolio is 58 basis points per month across the three models. Over a six-month holding period, this adds up to approximately $6 \times 58 = 348$ basis points. However, since insiders purchase only about 0.03 percent of all stock (see figure 1), the outsider's expected costs of trading against an insider are only $348 \times 0.0003 = 0.10$ basis points over the six-month period. Thus, for a $10,000 sale, she would be willing to pay about 10 cents to ensure that the trade did not have an insider as counterparty. This amount drops nearly to zero if the outsider is making a purchase from an insider. Although insiders make a much larger proportion of all sales than purchases, their abnormal returns on sales are small or nonexistent.

### *B. The Timing of Abnormal Returns*

We can better understand the dynamics of abnormal returns through a time decomposition of the purchase and sale portfolios. To illustrate this decomposition, consider the purchase portfolio. Recall that this shadow portfolio holds all insider purchases, using closing prices from their transaction dates, and keeps them in the portfolio for exactly 6 months. Now, we parse this strategy into portfolios that hold insider purchases for different subperiods during those 6 months: day0–day5, day5–day21, and day21–month6. That is, when an insider trade first occurs, it is placed in the first portfolio (day0–day5); then, at the end of day 5, the purchase is removed from the first portfolio and placed in the second portfolio (day5–day21); etc. The days here are trading days; thus 21 days is approximately 1 month. We follow the same procedure to decompose the sale portfolio.

TABLE 2.—PERFORMANCE-EVALUATION RESULTS FOR TIME DECOMPOSITIONS OF THE PURCHASE AND SALE PORTFOLIOS

| | Purchase | Sale |
|---|---|---|
| CAPM | | |
| day0–day5 | 0.0282** | 0.0079** |
| | (0.0031) | (0.0021) |
| day5–day21 | 0.0154** | −0.0008 |
| | (0.0023) | (0.0017) |
| day21–month6 | 0.0048** | −0.0023 |
| | (0.0018) | (0.0014) |
| Four-Factor Model | | |
| day0–day5 | 0.0255** | 0.0094** |
| | (0.0031) | (0.0020) |
| day5–day21 | 0.0139** | −0.0008 |
| | (0.0022) | (0.0015) |
| day21–month6 | 0.0032* | −0.0011 |
| | (0.0014) | (0.0011) |
| CS Measure | | |
| day0–day5 | 0.0314** | 0.0088** |
| | (0.0029) | (0.0017) |
| day5–day21 | 0.0162** | 0.0005 |
| | (0.0022) | (0.0014) |
| day21–month6 | 0.0029* | −0.0009 |
| | (0.0014) | (0.0010) |

The bottom half of the table presents the performance-evaluation results for decompositions of the purchase and sale portfolios into three holding periods: day0–day5, day5–day21, and day21–month6. At the close of trading on the day that an insider transaction occurs, the purchase or sale is placed in the day0–day5 portfolio; at the end of day 5, the trade is removed from the previous portfolio and placed in the day5–day21 portfolio; and so on. This decomposition is done separately for purchases and sales. The top of the chart shows the regression intercepts α from the CAPM [equation (1)]. The middle shows the regression intercepts α from the four-factor model [equation (2)]. The bottom shows the CS measure [equation (3)]. Standard errors appear in parentheses. The symbols * and ** indicate two-tail significance at the 5% and 1% levels, respectively. The sample is from January 1, 1976 to May 31, 1996.

Table 2 gives performance measures and standard errors for the day0–day5, day5–day21, and day21–month6 purchase and sale portfolios. The top panel gives the CAPM α's, the middle panel gives the four-factor α's and the bottom panel gives the CS measures. The day0–day5 purchase portfolio has highly significant positive point estimates across all models; these estimates range between 255 and 314 basis points per month. These returns illustrate the importance of using daily data to evaluate insider performance; any study that starts on report dates or uses only monthly data will miss this effect. These monthly abnormal returns translate into daily abnormal returns of about 13 basis points, or about 65 basis points over five trading days. Whether this is seen as economically large depends on the context. For example, the day0–day5 portfolio completely turns over every five trading days, far more often than any of the other portfolios studied in this paper. Assuming a 1% round-trip transaction cost, the day0–day5 portfolio would incur approximately 400 basis points in transaction costs per month. Thus, the abnormal returns are not sufficient to allow a profitable trading strategy after transaction costs, even if such a trading strategy were otherwise feasible.

The purchase portfolio continues to earn abnormal returns well beyond 5 days. The day5–day21 portfolio earns

TABLE 3.—PERFORMANCE-EVALUATION RESULTS FOR TRADE-VOLUME DECOMPOSITIONS OF THE PURCHASE AND SALE PORTFOLIOS

| | Purchase | Sale |
|---|---|---|
| CAPM | | |
| Low-volume | 0.0022** | −0.0024** |
| | (0.0007) | (0.0008) |
| Medium-volume | 0.0074** | −0.0024 |
| | (0.0013) | (0.0012) |
| High-volume | 0.0070** | −0.0008 |
| | (0.0020) | (0.0017) |
| Four-Factor Model | | |
| Low-volume | 0.0026** | −0.0011 |
| | (0.0007) | (0.0007) |
| Medium-volume | 0.0060** | −0.0012 |
| | (0.0009) | (0.0010) |
| High-volume | 0.0053** | −0.0001 |
| | (0.0016) | (0.0012) |
| CS Measure | | |
| Low-volume | 0.0026** | −0.0007 |
| | (0.0006) | (0.0006) |
| Medium-volume | 0.0078** | −0.0011 |
| | (0.0009) | (0.0009) |
| High-volume | 0.0051** | 0.0004 |
| | (0.0017) | (0.0012) |

This table presents the performance-evaluation results for decompositions of the purchase and sale portfolios by trade volume. To form our component portfolios, we first calculate the percentage of firm equity traded in each transaction. Next, we sort all trades by these equity percentages, with purchases and sales ranked separately. Based on these rankings, we divide purchases and sales into thirds: "low-volume," "medium-volume," and "high-volume." This yields cutoffs of 0.004% and 0.026% for the purchase thirds, and 0.010% and 0.047% for the sales thirds; that is, all sales below 0.010% of firm equity are classified as low-volume, above 0.047% as high-volume, and in between as medium-volume. The top of the table shows the regression intercepts $\alpha$ from the CAPM [equation (1)]. The middle shows the regression intercepts $\alpha$ from the four-factor model [equation (2)]. The bottom shows the CS measure [equation (3)]. Standard errors appear in parentheses. The symbols * and ** indicate two-tail significance at the 5% and 1% levels, respectively. The sample is from January 1, 1976 to May 31, 1996.

significant abnormal returns of 154 basis points under the CAPM, 139 under the four-factor model, and 162 for the CS measure. For most insider transactions, more than 21 days pass before the transactions get reported and made public. The corresponding estimates for the day21–month6 portfolio are 48 basis points for the CAPM, 32 for the four-factor model, and 29 for the CS measure. All of these $\alpha$ estimates are significant. The point estimates from table 2 enable us to approximately decompose the overall abnormal returns to the purchase portfolio; using either the CS measure or the four-factor $\alpha$ as our guide, about one-quarter comes in the first 5 days and one-half comes in the first month.[27]

The most striking results of table 2 are found for the day0–day5 sale portfolio. At longer horizons, sale portfolios fail to earn significant abnormal returns, with the $\alpha$'s and CS measures economically close to zero in most cases. The abnormal performance for the day0–day5 portfolio is positive and significant under all models, with point estimates ranging between 79 and 94 basis points per month. These results seem counterintuitive; why would the stocks that insiders sell perform so well over the subsequent five days? In section VA, we present evidence to show that these short-horizon returns can be explained by the recovery from the price-depressing effect of high-volume insider sales. That is, the patterns are consistent with a market microstructure effect.

Although the analysis in this paper is uses a 6-month horizon as motivated by the short-swing rule, it is also interesting to see if the abnormal returns persist beyond this time. In untabulated results, we analyze purchase and sale portfolios over the month6–year1 and year1–year3 horizons. We find that neither the purchase nor sale portfolios earn significant abnormal returns over these horizons, with economically small point estimates in all cases. Thus, we conclude that the abnormal returns to insider trading accrue within the first six months, and do not reverse or increase afterwards.

## V. Do Abnormal Returns Differ among Different Types of Trades?

Thus far, we have confined our analysis to the aggregate purchase and sale portfolios. In this section, we decompose the purchase and sale portfolios along five dimensions: volume of the trade, size of the firm, book-to-market ratio of the firm, insider's position in the firm, and whether the trade is executed directly for an insider or indirectly for another party.

### A. *The Volume of a Trade*

Past research has generally found a positive relationship between trade volume and insider informativeness, although this relationship may break down for the highest-volume trades.[28] In this subsection, we examine the relationship between trade volume and insider returns. There are logical reasons to believe that the highest-volume trades would reflect the strongest insider beliefs about corporate performance. However, such trades may have other motivations. For example, insiders with sizable corporate holdings may undertake high-volume sales for diversification or liquidity purposes; such sales may be motivated more by a desire to reduce risk or buy a new house than to increase returns. Also, high-volume purchases may be related to a quest for corporate control and its nonpecuniary benefits, and may only partially be related to expectations of future returns. On a more cynical note, one might believe that high-volume trades are more likely to be scrutinized by the SEC, so that insiders who report trades on illegal inside information may

[27] The four-factor $\alpha$ estimate for the overall purchase portfolio (table 3) is 52 basis points per month, or approximately 312 basis points for six months. Since the point estimate for the day21–month6 portfolio is 32 basis points, we attribute $32 \times 5 = 160$ of the total to the last five months. Similar calculations for the other horizons yield the estimates in the text.

[28] See Seyhun (1986), Pascutti (1996), and Seyhun (1998). Jaffe (1974) finds no difference between overall tests and tests restricted to high-volume trades, but this may be due to his sample of only the largest NYSE firms, where the trade-volume effect has been found to be weakest (Seyhun, 1998).

wish to take lower profits, by reducing or splintering trades, in order to reduce the probability of detection. These factors all militate against finding the highest-volume trades having the highest abnormal returns.

We begin by decomposing the purchase and sale portfolios by trade volume into *low-volume*, *medium-volume*, and *high-volume* purchase and sale portfolios. To form these portfolios, we first calculate the fraction of firm equity traded in each transaction. For example, a purchase of 10,000 shares of a stock with 100 million shares outstanding would represent 0.01% of equity. Next, we sort all trades by these equity fractions, with purchases and sales ranked separately. Based on these rankings, we divide purchases and sales into thirds: *low, medium,* and *high.* This yields cutoffs of 0.004% and 0.026% for the purchase portfolios, and 0.010% and 0.047% for the sale portfolios. That is, all sales below 0.010% of firm equity are classified as low-volume, above 0.047% are classified as high-volume, and in between as medium-volume.[29] For our purposes, this procedure offers two advantages over simpler classifications based on absolute measures such as the number of shares or dollars traded. First, the absolute measures are highly correlated with firm size, and analyses based on them might confound firm-size and trade-volume effects. Our use of equity fractions mitigates this problem. Second, our approach increases the chance that trades with a large market impact are classified as high-volume.[30] The importance of this property will be seen below.

The performance measures for the trade-volume portfolios are summarized in table 3. To compare estimates across the different portfolios, we estimate each model as a seemingly unrelated regression (SUR) for the six decomposed purchase and sale portfolios; this framework provides estimates for the covariance of the performance measures.[31] The abnormal returns for the high-volume and medium-volume purchase portfolios are economically large and statistically significant on all tests, with magnitudes that are similar both to each other and to the overall purchase portfolio. The low-volume purchase portfolio earns considerably lower abnormal returns, although all measures are still positive and significant. Using covariance estimates from the SUR (not reported in table 3), we find that the medium-volume purchase portfolio achieves significantly higher performance measures on all three tests than does the low-volume purchase portfolio.

Performance measures for the sale portfolios are economically small and—with one exception—not statistically significant. Under the CAPM, the low-volume sale portfolio earns significant negative abnormal returns, with a relatively precise point estimate of −24 basis points. This precision derives from the well-diversified nature of the low-volume portfolio, which, by construction, cannot be dominated by a small number of positions. Note that there is no significant relationship between trade volume and returns for insider sales on any of the tests: none of the performance measures is significantly different from any other.

To shed light on the counterintuitive positive abnormal returns for the day0–day5 sale portfolio, we perform the same time decomposition for each trade-volume portfolio that we did in Section IVB for the overall purchase and sale portfolios. Table 4 illustrates the returns to the low-, medium-, and high-volume purchase and sale portfolios for the

TABLE 4.—PERFORMANCE-EVALUATION RESULTS FOR TRADE-VOLUME DECOMPOSITIONS OF THE DAY0–DAY5 AND DAY5–MONTH6 PURCHASE AND SALE PORTFOLIOS

| | day0–day5 | | day5–month6 | |
|---|---|---|---|---|
| | Purchase | Sale | Purchase | Sale |
| CAPM | | | | |
| Low-volume | 0.0114** | −0.0057** | 0.0017* | −0.0023** |
| | (0.0018) | (0.0014) | (0.0007) | (0.0008) |
| Medium-volume | 0.0244** | −0.0044* | 0.0066** | −0.0023 |
| | (0.0025) | (0.0021) | (0.0013) | (0.0012) |
| High-volume | 0.0318** | 0.0129** | 0.0061** | −0.0018 |
| | (0.0039) | (0.0027) | (0.0020) | (0.0017) |
| Four-Factor Model | | | | |
| Low-volume | 0.0107** | −0.0042* | 0.0021** | −0.0010 |
| | (0.0019) | (0.0014) | (0.0008) | (0.0007) |
| Medium-volume | 0.0229** | −0.0035 | 0.0052** | −0.0012 |
| | (0.0025) | (0.0020) | (0.0009) | (0.0010) |
| High-volume | 0.0285** | 0.0143** | 0.0044** | −0.0009 |
| | (0.0039) | (0.0026) | (0.0016) | (0.0012) |
| CS Measure | | | | |
| Low-volume | 0.0121** | −0.0038* | 0.0022** | −0.0006 |
| | (0.0018) | (0.0012) | (0.0006) | (0.0006) |
| Medium-volume | 0.0277** | −0.0023 | 0.0068** | −0.0011 |
| | (0.0029) | (0.0018) | (0.0009) | (0.0010) |
| High-volume | 0.0366** | 0.0137** | 0.0043* | −0.0007 |
| | (0.0040) | (0.0023) | (0.0017) | (0.0012) |

This table presents the performance-evaluation results for decompositions of the day0–day5 purchase and sale portfolios and day5–month6 purchase and sale portfolios by trade volume. The day0–day5 purchase (sale) portfolio includes all shares purchased (sold) by insiders over the previous five days. The day5–month6 portfolio contains all trades in the day0–day5 portfolio at the end of day 5 and holds each trade for a period equal to six months after the first day of the insider transaction. To decompose these portfolios by trade volume, we first calculate the percentage of firm equity traded in each transaction. Next, we sort all trades by these equity percentages, with purchases and sales ranked separately. Based on these rankings, we divide purchases and sales into thirds: low-volume, medium-volume, and high-volume. This yields cutoffs of 0.004% and 0.026% for the purchase thirds, and 0.010% and 0.047% for the sales thirds; that is, all sales below 0.010% of firm equity are classified as low-volume, above 0.047% as high-volume, and in between as medium-volume. The top of the table shows the regression intercepts α from the CAPM [equation (1)]. The middle shows the regression intercepts α from the four-factor model [equation (2)]. The bottom shows the CS measure [equation (3)]. Standard errors appear in parentheses. The symbols * and ** indicate two-tail significance at the 5% and 1% levels, respectively. The sample is from January 1, 1976 to May 31, 1996.

[29] We use the whole sample period to make these cutoffs, but this procedure—which looks forward as well as backward—should not introduce any bias in this case.

[30] Trades could also be classified using dollar trading volume (rather than firm equity) in the denominator. Unfortunately, CRSP does not include volume data for Nasdaq firms until 1983, so this method is not feasible.

[31] In our case, the SUR approach yields exactly the same point estimates and standard errors as would separate estimations, and provides the covariance estimates necessary for our comparisons. Another method to compare performance measures is to evaluate the returns to zero-investment strategies that are long in one portfolio (say low-volume purchases) and short in another (say medium-volume purchases). The SUR and zero-investment approaches are mathematically equivalent.

day0–day5 subperiod. We also combine the other subperiods into a day5–month6 decomposition for each of the volume portfolios.

The table gives compelling evidence that the positive abnormal returns earned by the day0–day5 sale portfolio are driven by the highest-volume transactions. The high-volume sale portfolio has positive and significant performance measures under all models, with point estimates ranging from 129 to 143 basis points. The performance measures for the low-volume sale portfolio are negative and significant under all models; this is the direction that would be expected when insiders make information-driven trades. When results are examined over the remaining day5–month6 subperiod, the high-volume sale portfolio earns insignificant abnormal returns under all specifications.

Our hypothesis is that the high-volume sales are driven primarily by liquidity or diversification motives, and that these big trades cause downward price pressure, so that the day0–day5 abnormal returns are positive while the market bounces back from this pressure.[32] Since price pressure is small or nonexistent for medium- and low-volume trades, we do not observe the same positive abnormal returns for those portfolios. Since the high-volume trades dominate the value-weighted sale portfolio, they are capable of driving the perverse short-run effect.

These results raise two questions. First, if the price pressure effect is so strong for the sale portfolio, why don't we see a symmetric effect for the purchase portfolio? Second, might these day0–day5 results be driven by short-run negative autocorrelation of individual stocks? We discuss these two questions below.

In contrast to the high-volume sale portfolio, the high-volume purchase portfolio appears to suffer no drag on performance due to price pressure: over the day0–day5 period, the high-volume purchase portfolio earns significantly positive abnormal returns between 285 and 366 basis points per month—higher than the abnormal returns of either the low-volume or the medium-volume portfolios. Indeed, the difference between the $\alpha$'s of the low-volume and high-volume portfolios has the same sign and nearly the same magnitude for purchases as it has for sales—yet the price pressure should be pushing these differences to have opposite signs. There are two reasons for this asymmetry. First, the trade-volume cutoffs for these portfolios are very different, with the 0.026% cutoff for the high-volume purchase portfolio lying somewhere in the middle of the medium-volume sale portfolio. The cutoff for the high-volume sale portfolio, 0.047%, is reached by one-third of all sales but only 23% of all purchases. Other reasons for the asymmetry are that the very rarity of the highest-volume purchases is likely to greatly magnify their information content and that, in contrast to high-volume sales, firms have an incentive to release information on such purchases before they are legally required to do so. If the purchase is publicly revealed within five days, then this revelation can further increase the stock price. In sum, there are several good reasons why price pressure might wash out for the purchase portfolios.

Might all of these day0–day5 results be driven by short-run negative autocorrelation of individual stocks?[33] Such autocorrelation is demonstrated at the weekly horizon by Lehman (1990) and at the monthly horizon by Jegadeesh (1990). To the extent that insider transactions are preceded by significant market moves—as suggested by figure 2 in section II—some of the subsequent profits or losses earned by insiders may simply be an artifact of negative autocorrelation.

In investigate this possibility more rigorously, we employ a time decomposition of the low-volume, medium-volume, and high-volume purchase and sale portfolios for the one-week period *preceding* the insider transaction. To avoid possible confounds from intraday effects, we do not include the day of the reported transaction, and compute the day($-5$)–day($-1$) decomposition. Consistent with the evidence of figure 2, we find that all of the sale portfolios earn significantly positive abnormal returns and all of the purchase portfolios earn significantly negative returns during this time period: that is, insiders sell stocks that have recently gone up, and buy stocks that have recently fallen.[34]

Can these results, combined with evidence of negative autocorrelation, help to reconcile the day0–day5 abnormal returns? Because the high-volume sale portfolio earns positive abnormal returns in the first five days, it displays positive autocorrelation and cannot be explained by a reversal. As discussed above, this positive return seems to be the result of price pressure. For the low-volume and medium-volume portfolios, however, the negative abnormal return of the day0–day5 portfolios is consistent with negative autocorrelation. The magnitudes of these negative abnormal returns, shown in table 4, are not qualitatively different than abnormal returns achievable from a strategy of shorting the winner stocks of the previous week (Lehmann, 1990). Thus, it appears that negative autocorrelation can explain some, if not all, of the results for the day0–day5 sale portfolios.

Negative autocorrelation may also explain some of the day0–day5 abnormal returns in the purchase portfolio, but the importance of this mechanism is proportionally much smaller than it is for the sale portfolios. For the purchase portfolio, we find that the day($-5$)–day($-1$) abnormal returns are approximately the same magnitude as the day0–day5 abnormal returns. To reconcile these magnitudes would require a nearly complete return reversal over a 1 week horizon: a result far stronger than found by Lehmann (1990). Furthermore, for the day($-5$)–day($-1$) decomposition, we find that the low-volume purchase portfolio

[32] This kind of volume-based autocorrelation is documented in Conrad, Hameed, and Niden (1994).

[33] We are grateful to the referee for pointing out this possibility.

[34] Detailed results for all day($-5$)–day($-1$) estimations are available from the authors.

performs worse than the high-volume purchase portfolio; that is, low-volume purchases are preceded by lower returns than are high-volume purchases. Thus, negative autocorrelation at the weekly horizon would imply that the low-volume purchase portfolio should perform better than the high-volume purchase portfolio over the day0–day5 period, whereas table 4 demonstrates that the opposite is true. Overall, we conclude that the profits earned by purchases—especially high-volume purchases—are mostly due to superior information of insiders.

### B. *Firm Size*

Several studies that use intensive-trading criteria and event-study methods show that insider trading is most informative in small firms (Seyhun, 1986, 1998; Pascutti, 1996; Lakonishok and Lee, 2001). This empirical finding is consistent with intuition. The smaller the firm, the easier it is for a single manager to know a significant portion of the relevant information. And because small firms receive less attention than large firms do from Wall Street analysts, the smaller the firm, the more likely that insiders hold an informational advantage over other market participants.

We analyze the relationship between firm size and insider returns by decomposing the purchase and sale portfolios. At the beginning of each month, we divide the stocks traded on the NYSE into thirds based on size (market value). We then use the cutoffs for these thirds to place all NYSE, AMEX, and Nasdaq stocks into one of three categories: *small-firm, medium-firm,* and *large-firm.* Each insider transaction is then placed in a portfolio on the day of the trade based on the size of the firm. This holding stays in the same portfolio for the full 6 months, even if the firm crosses a size cutoff. This procedure results in six portfolios (three for purchases and three for sales). We then compute the returns to these portfolios and use these returns in the same performance-attribution models used in the previous analyses.

We present the size results in table 5. As would be expected from the other results of this paper, none of the sale portfolios earn significant abnormal returns under any of the methods. The results are more interesting for the purchase portfolios. The small-firm purchase portfolio earns significant abnormal returns under all three methods, with point estimates ranging between 31 and 49 basis points per month. None of the other purchase portfolios earns significant abnormal returns on any test. Nevertheless, the performance measures for the small-firm purchase portfolio are never significantly different from the corresponding measures for either the medium- or large-firm purchase portfolios.[35] In fact, the biggest difference occurs under the CAPM (49 basis points for small-firm purchases versus 16 basis points for large-firm purchases), and some of this is certainly attributable to the small-firm anomaly in the CAPM.[36] Under the four-factor model, the difference in abnormal returns between the small- and large-firm purchase portfolios drops by roughly one-quarter (relative to the CAPM difference), and for the CS measure it disappears completely. Thus, and not surprisingly, the marginal effect of firm size on insider returns is considerably smaller (or nonexistent) once we control for size-related return anomalies.[37] These results are not driven by our use of only three size portfolios: there remains no significant difference between the performance measures (four-factor $\alpha$'s and CS measures) of the smallest and largest purchase portfolios even if we use five or ten size groupings.[38]

TABLE 5.—PERFORMANCE-EVALUATION RESULTS FOR FIRM-SIZE DECOMPOSITIONS OF THE PURCHASE AND SALE PORTFOLIOS

| | Purchase | Sale |
|---|---|---|
| CAPM | | |
| Small-firm | 0.0049* | 0.0003 |
| | (0.0019) | (0.0021) |
| Medium-firm | 0.0050 | −0.0008 |
| | (0.0029) | (0.0017) |
| Large-firm | 0.0016 | −0.0015 |
| | (0.0021) | (0.0013) |
| Four-Factor Model | | |
| Small-firm | 0.0037** | 0.0013 |
| | (0.0013) | (0.0012) |
| Medium-firm | 0.0043 | 0.0004 |
| | (0.0028) | (0.0014) |
| Large-firm | 0.0012 | 0.0000 |
| | (0.0021) | (0.0013) |
| CS Measure | | |
| Small-firm | 0.0031* | 0.0012 |
| | (0.0013) | (0.0011) |
| Medium-firm | 0.0044 | −0.0008 |
| | (0.0025) | (0.0012) |
| Large-firm | 0.0034 | 0.0003 |
| | (0.0018) | (0.0012) |

This table presents the performance-evaluation results for decompositions of the purchase and sale portfolios by firm size. At the beginning of each month, we divide the NYSE into thirds based on size (market value). We then use the cutoffs for these thirds to place all NYSE, AMEX, and Nasdaq stocks in one of three categories: small-firm, medium-firm, and large-firm. Each insider transaction is then placed in a portfolio on the day of the trade based on the size of the firm. This position stays in the same portfolio for 6 months, even if the underlying firm crosses a size cutoff. This procedure results in six portfolios (three for purchases and three for sales). The top of the table shows the regression intercepts $\alpha$ from the CAPM [equation (1)]. The middle shows the regression intercepts $\alpha$ from the four-factor model [equation (2)]. The bottom shows the CS measure [equation (3)]. Standard errors appear in parentheses. The symbols * and ** indicate two-tail significance at the 5% and 1% levels, respectively. The sample is from January 1, 1976 to May 31, 1996.

In section 4, we computed the expected cost of trading against insiders to be approximately 0.10 basis points over a 6-month period. This computation used the expected profits and fraction of trades in all stocks. Since the fraction traded by insiders is likely to be much greater for small stocks, it is worthwhile to repeat this calculation for that class. We find that insiders purchases approximately 0.14%

[35] This comparison uses covariances of the performance measures (not reported in the table) estimated by SUR.

[36] See Banz (1981) and Fama and French (1993).

[37] This same point is made by Rozeff and Zaman (1988), although their focus is on informativeness.

[38] These results are available from the authors.

of the average daily volume in small stocks. Table 5 shows that, across the three models, stocks sold to insiders in small firms tend to outperform benchmarks by approximately 39 basis points per month, on average. Over six months, this implies 234 basis points, implying expected losses of approximately $234 \times 0.0014 = 0.33$ basis points for outsiders. This is more than triple the level of expected losses in all stocks, but is still very small in economic terms.

### *C. Firm Book-to-Market Ratio*

A long line of research demonstrates that value characteristics—price-earning ratios, BM ratios—can predict relative stock price performance.[39] The evidence that high-BM firms outperform low-BM firms—the *value premium*—was one impetus for the multifactor models developed in the last decade and used for performance evaluation in this paper.

Researchers have proposed two possible explanations for the value premium. A *risk* explanation posits that the value premium is earned by higher exposures to some priced risk factor. A *mispricing* explanation is that a high BM ratio signals that the market is, on average, undervaluing the assets of the firm. At first glance, it appears that insider-trading data can help resolve this debate: if insiders predominantly buy stock in high-BM firms and sell stock in low-BM firms, then this could be interpreted as a signal that informed investors believe high-BM stocks to be undervalued and low-BM stocks to be overvalued. Indeed, this is the general pattern of insider activity found by Seyhun (1998). Unfortunately, inference is clouded here by the differential holdings of insiders in high-BM and low-BM firms: since low-BM firms tend to be younger and more closely held than are high-BM firms, one would expect more insider selling and less insider buying, other things equal. In order to detect important differences, one would need to know these holding levels for all firms, and also make assumptions about risk aversion and outside wealth holdings for all managers—variables that may indeed differ by firm type. Thus, it is difficult for insider-trading patterns to contribute directly to the debate on the source of the value premium.

Even though the level of insider trading cannot be used to resolve the value-premium debate, the relative profits of insiders in high-BM and low-BM firms is still an interesting area of study. If at least some high-BM stocks are mispriced, then we might expect managers to be able to identify this mispricing and concentrate their trading in those stocks. For stock repurchases by firms, this is exactly the observed pattern: using event-study methodology, Ikenberry, Lakonishok, and Vermaelen (1995) find that high-BM firms exhibit a significantly positive abnormal return in the four years following repurchases, whereas low-BM firms do not. If managers can succeed with such market timing for the firm's account, then they may be able to do so with their own trades as well.

On the other hand, it is also reasonable to expect that the highest insider profits occur for the low-BM firms. Using an intensive-trading filter rule, Aboody and Lev (2000) find that insider gains in high-R&D firms are higher than those in low-R&D firms. The intuition for this result is that high R&D is signal of high asymmetric information and potential for superior information by managers. To the extent that low-BM firms—ostensibly those with the highest growth opportunities—have higher levels of R&D than do high-BM firms, then we might expect to find profits to be higher there as well. Finally, Seyhun (1998) finds that the intensity of insider trading is informative in both low-BM and high-BM firms, even after adjusting for size and value effects.

Following the same methodology as in the previous subsection, we analyze the relationship between a firm's BM ratio and insider returns by decomposing the purchase and sale portfolios. In July of each year, we divide the stocks traded on the NYSE into thirds based on their BM. We then use the cutoffs for these thirds to place all NYSE, AMEX, and Nasdaq stocks into one of three categories: *low-BM*, *medium-BM*, and *high-BM*. Each insider transaction is then placed in a portfolio on the day of the trade based on the size of the firm. This holding stays in the same portfolio for the full 6 months, even if that period extends over a July date and the firm changes thirds. This procedure results in six portfolios (three for purchases and three for sales). We then compute the returns to these portfolios and use these returns in the same performance-attribution models used in the previous analyses.

Table 6 summarizes the results. As in almost all previous cases, none of the sale portfolios earns significant abnormal returns in any of the specifications. For the purchase portfolios, under the CAPM specification only the medium-BM portfolio earns significant abnormal returns, although both the low-BM and high-BM portfolios also have positive $\alpha$'s. Since these portfolios are effectively being sorted by one of the multifactor attributes, we might expect the results to change once these factors are included. Indeed, both the four-factor and CS measure results suggest that the highest abnormal returns are earned by the low-BM portfolio. Under the four-factor model, none of the portfolios earn significant abnormal returns, but the low-BM portfolio has an $\alpha$ that is 34 basis points per month higher than the one for the high-BM portfolio. For the CS measure, the low-BM portfolio earns a positive and significant abnormal return of 38 basis points per month, whereas the high-BM portfolio earns an insignificant abnormal return of 11 basis points per month. Overall, there is some weak evidence that, after adjusting for the value premium, insiders in low-BM firms earn higher profits than do insiders in high-BM firms. Although none of these differences are significant, there is no evidence in the other direction.

[39] This literature dates back to the classic text by Graham and Dodd (1934). Influential academic papers include Basu (1977), Fama and French (1993), and Lakonishok, Shleifer, and Vishny (1994).

TABLE 6.—PERFORMANCE-EVALUATION RESULTS FOR BOOK-TO-MARKET DECOMPOSITIONS OF THE PURCHASE AND SALE PORTFOLIOS

| | Purchase | Sale |
|---|---|---|
| CAPM | | |
| Low-BM | 0.0016 | −0.0013 |
| | (0.0018) | (0.0015) |
| Medium-BM | 0.0037* | −0.0001 |
| | (0.0016) | (0.0013) |
| High-BM | 0.0029 | −0.0009 |
| | (0.0029) | (0.0015) |
| Four-Factor Model | | |
| Low-BM | 0.0023 | 0.0004 |
| | (0.0014) | (0.0014) |
| Medium-BM | 0.0021 | −0.0010 |
| | (0.0011) | (0.0010) |
| High-BM | −0.0011 | −0.0016 |
| | (0.0026) | (0.0011) |
| CS Measure | | |
| Low-BM | 0.0038* | 0.0002 |
| | (0.0013) | (0.0012) |
| Medium-BM | 0.0025 | −0.0003 |
| | (0.0011) | (0.0009) |
| High-BM | 0.0011 | 0.0002 |
| | (0.0021) | (0.0010) |

This table presents the performance-evaluation results for decompositions of the purchase and sale portfolios by book-to-market ratio. At the beginning of each month, we divide the NYSE into thirds based on book-to-market ratio. We then use the cutoffs for these thirds to place all NYSE, AMEX, and Nasdaq stocks into one of three categories: low-BM, medium-BM, and high-BM. Each insider transaction is then placed in a portfolio on the day of the trade based on the book-to-market ratio of the firm. This position stays in the same portfolio for six months, even if the underlying firm crosses a book-to-market ratio cutoff. This procedure results in six portfolios (three for purchases and three for sales). The top of the table shows the regression intercepts α from the CAPM [equation (1)]. The middle shows the regression intercepts α from the four-factor model [equation (2)]. The bottom shows the CS measure [equation (3)]. Standard errors appear in parentheses. The symbols * and ** indicate two-tail significance at the 5% and 1% levels, respectively. The sample is from January 1, 1976 to May 31, 1996.

Next, we compute the expected losses to outsiders in the special classes of small-value and small-growth stocks. We use the intersection of small-firm (from table 5) with both low-BM and high-BM (from table 6) purchase portfolios, labeling the first intersection as “small value” and the second intersection as “small growth.” We then compute the returns to these portfolios and use these returns in the same performance-attribution models used in the previous analyses. Across the three models, the monthly abnormal returns for these portfolios average 30 basis points for small value and 25 basis points for small growth, implying 6-month abnormal returns of 180 basis points and 150 basis points, respectively.[40] We also find that insiders purchase approximately 0.20% of the average daily volume in small-value stocks and 0.12% in small-growth stocks. Thus, the expected losses to outsiders are $180 \times 0.0020 = 0.36$ basis points for small value and $150 \times 0.0012 = 0.18$ basis points for small growth. On a $10,000 transaction, these expected losses correspond to 36 cents and 18 cents, respectively.

[40] Details of these estimations are available upon request.

### D. *Insider’s Position within the Firm*

Some insiders are more inside than others. The chief executive, for example, is likely to have better information about the firm’s prospects than do lesser officers. Of course, since the CEO’s trades are likely to be carefully scrutinized, both by shareholders and by regulators, he may be more reluctant to trade on his informational advantage. The net effect of these considerations on the returns to different insiders’ trading is an empirical question. Seyhun (1986, 1998) analyzes the relationship between insiders’ positions in their firms and the informativeness of their trades, and concludes that there is an *information hierarchy,* with top executives at the top, other officers in the middle, and directors at the bottom. In this section we study whether this information hierarchy extends to the returns earned by insiders themselves.

We begin by decomposing the purchase and sale portfolios according to the job title of the insider. *Top executives* are chief executives, chairmen of the board, and presidents. *Officers* include all corporate officers except for top executives. *Directors* are members of the corporate board who are not also officers. These categories do not overlap, and they cover all trades in our sample.[41] This decomposition results in three purchase portfolios and three sale portfolios. The top-executive purchase portfolio constitutes 10.4% of the total purchase portfolio, the officer-purchase portfolio 19.3%, and the director-purchase portfolio 70.3%. Top executives account for 12.2% of sales, officers 41.8% and directors 46.0%.

We next estimate performance measures for these portfolios. We estimate each model as a SUR, so that performance estimates can be compared across portfolios. The results are summarized in the text below, with details available upon request. None of the sale portfolios earns significant abnormal returns on any of the tests. As usual, the purchase portfolios offer more varied results. The officer-purchase and director-purchase portfolios have significant abnormal returns under all tests, with point estimates close to those found for the overall purchase portfolio. The top-executive purchase portfolio earns significant abnormal returns under the CAPM and four-factor models. Overall, there is no evidence that the top executives earn higher abnormal returns than do other officers and directors. Of course, top executives’ trades tend to be of higher volume than those of other officers and directors, so they may indeed be taking out some rents through higher dollar returns per trade.

[41] These definitions differ slightly from Seyhun’s (1998), which do allow for overlap. Some insiders do not fit into any of these categories. We exclude them from the beginning; they are not represented in the purchase and sale portfolios. See appendix A.

### *E. Direct versus Indirect Ownership of Shares*

Insiders' holdings can be subdivided into two broad categories. *Direct* holdings are held in the insider's name. *Indirect* holdings are held in the name of another person, and the corporate insider has a pecuniary interest by reason of a contract, understanding, or relationship.[42] With the exception of Pascutti (1996), past studies of insider trading have not distinguished between these two types of ownership.

In this subsection, we divide the sale and purchase portfolios into their direct and indirect components. Thus, the direct-purchase portfolio contains all purchases for direct holdings made over the previous six months; the other portfolios are indirect-purchase, direct-sale, and indirect-sale. The direct portfolios comprise the majority of both the purchase and sale portfolios, but the indirect portfolios are still substantial, comprising 42.7% of the purchase portfolio and 22.1% of the sale portfolio.

It is not obvious what to expect for the relative performance of direct and indirect portfolios. For direct trades, insiders are likely to exercise total discretionary control and keep all the proceeds. In many indirect trades, insiders exercise considerably less discretion and have smaller personal incentives. This suggests that direct trades would be more likely to reflect insider information and yield higher abnormal returns.

However, insiders make many of their direct trades—particularly those of high volume—to diversify their portfolios or increase their control of the corporation. Indirect trades, on the other hand, are less likely to be driven by considerations of control or diversification, especially in that indirect holders usually do not have their human capital invested in the firm. Similarly, purchases designed to increase control are probably more likely for a direct holding than for an indirect one. Since these considerations are stronger for high-volume transactions, they have the potential to dominate a value-weighted analysis. This reasoning suggests that abnormal returns would be higher for indirect trades than for direct ones.

We next estimate performance measures for these portfolios. We again estimate each model as a SUR so that performance estimates can be compared across portfolios. The results are summarized in the text below, with details available upon request. The CAPM $\alpha$ for the direct-purchase portfolio is 79 basis points; the corresponding $\alpha$ for the indirect-purchase portfolio is 71 basis points. These point estimates are significantly different from zero, but not from each other. The four-factor $\alpha$'s and CS measures show a similar pattern. The direct-purchase portfolio earns a four-factor $\alpha$ of 64 basis points and a CS measure of 76 basis points, both of which are significant. The indirect-purchase portfolio has a four-factor $\alpha$ of 53 basis points and a CS measure of 52 basis points. For each of the three tests, the performance measure for the direct-purchase portfolio has a higher point estimate than the corresponding measure for the indirect-purchase portfolio, but the difference is never significant. For the direct-sale and indirect-sale portfolios, all of the performance measures are economically small and statistically insignificant. Overall, there is no significant evidence of differential abnormal returns between direct and indirect trades.

[42] See Goodman (1991).

## VI. Conclusion

There are three good reasons to study reported insider trading: science, profit, and policy. Science examines the implications of the findings for market efficiency. Profit hopes to develop optimal trading strategies, following the actions of insiders. Policy seeks to determine the effectiveness of insider-trading rules, and the implications of any insider advantages for both fairness and market performance.

Our analysis focused on science and policy. It began with the central question: When corporate insiders trade their company's stock, what returns do they earn? Although data limitations make it impossible to give an exact answer to this question, we construct a proxy by exploiting the short-swing rule of the Securities and Exchange Act of 1934. Since this rule prevents insiders from keeping any profits earned in offsetting trades within six months of each other, we assume that all trades are held for six months and then compute returns to value-weighted portfolios composed of all insider trades. We then analyze these returns using modern performance-evaluation methods.

Insiders' transactions differ from the market as a whole. Insiders disproportionately purchase shares in small firms, value firms, and those that have recently underperformed. Their sales are made mainly in growth firms that have experienced high recent returns. To correct for differences in returns that may be driven entirely by these distinctive characteristics of insider transactions, we calculated abnormal returns using three different performance-evaluation methods. Under all three methods, the story is much the same. The point estimates of the abnormal returns to a value-weighted portfolio of all insider purchases—holding positions for 6 months—are between 52 and 68 basis points per month, an economically and statistically significant magnitude. The first five days after purchase yield approximately one-quarter of the abnormal return, and about one-half comes within the first month. This evidence suggests that insider buyers have a good feel for near-term developments within their firm, and/or that actions by others who follow their trades move the market. None of our methods find abnormal returns for the sale portfolio. If the any of the performance-evaluation methods are interpreted as an equilibrium asset-pricing model, then the results for the purchase portfolio provide evidence against the strong form of market efficiency under that model.

Our performance-evaluation methods can readily determine whether particular types of trades do better or worse. Thus, we look at abnormal returns by firm size, trade volume, and the insider's position within the firm. We find that the trades of top executives do not earn higher abnormal returns than do those of their less lofty peers. Similarly, firm size does not significantly affect abnormal returns. We do find that low-volume purchases have smaller abnormal returns than those of higher volume.

Our analysis does not attempt to look at the potential for profit by following insiders' trades; other methods are better suited to that investigation, and the prior literature has covered them well. The potential for profit by outsiders is based on the informativeness of insider trading for future returns. Informativeness is typically tested using various filter rules about the intensity of insider trading. The resulting abnormal-return estimates average across all firms (not trades) and are conceptually distinct from the returns earned by insiders themselves. Although it is true that our value-weighted trades-based approach is just one special type of filter rule—a rule where every trade is included with a weight equal to its dollar value—it is different from other rules along several critical dimensions in ways that are specifically designed to measure insider profits, a measurement that is not possible nor attempted with intensive-trading criteria. Although some authors of previous studies do make qualitative claims about insider profits, these claims are not based on measurement of these profits, but instead are indirectly inferred from results about informativeness.

Our results show that even though several types of insider trading may be informative, they do not necessarily imply that insiders themselves earn abnormal returns. Insider sales are one example of this phenomenon: several filter rules based on insider sales have been found to be informative for future returns, but we find that our sale portfolio does not earn abnormal returns. Similarly, the purchases of top executives are found to be more informative than those of other insiders, but we find that top executives do not earn higher abnormal returns. There is nothing inconsistent about these pairings of results—the underlying questions and methods are different.

Nevertheless, many readers may be curious about the exact source of these differences—why exactly some types of trades are informative (like sales) but do not lead to much insider profit. There are several reasons. First, it is likely the very largest insider transactions are motivated by control or diversification motives, and not by special information. Such trades have much greater weight in our value-weighted analysis than in the equal-weighted analyses used by most other authors. Second, the filter rules used by the literature are designed to optimally pick out the situations where insider trading is most informative, whereas we take each trade as given. Third, our performance-evaluation techniques mean that we weight each time period equally, rather than weighting each trade (or firm) equally. If insiders are also market timers who tend to bunch their trades temporally, then our techniques may underestimate the higher profits at precisely the time when trades are most numerous.[43]

For these reasons, Loughran and Ritter (2000) refer to the features of value-weighting trades and equal-weighting time periods as "uniformly least powerful" for testing market efficiency. Low statistical power, however, is not the same as low economic power. Although our techniques may be least likely to detect a market anomaly or informative trade, they are well suited for measuring the average size of insider profits or outsider cost. Filter rules or alternative weighting schemes may be statistically powerful for detecting market anomalies; their drawback is that they provide no insight into the economic significance of a market anomaly. Finally, attempts to weight each trade (or firm) equally though event-study techniques run into the statistical difficulties analyzed by Barber and Lyon (1997), Barber et al. (1999), and Kothari and Warner (1997). Overall, it seems that both sets of techniques have their strengths and weaknesses, and are suited to answer different kinds of questions.

What should policymakers think of our results? Surely insiders have valuable information. If they do, only a draconian regulatory system could prevent them from trading profitably, and the evidence shows that the existing system does not. But the goal of policy should not be to prevent insiders from making profits, which would be prohibitively expensive even if desirable, but rather to protect outsiders from gross injury. Without such protection, outsiders may flee that market.

On this ground, policymakers can be reassured. The system is sufficiently effective so that outsiders are only slightly disadvantaged when selling stock on the open market, and they are not disadvantaged at all when buying. Inside purchases comprise just 0.03% of all purchases on the open market; on average, outsiders lose just 10 cents on a $10,000 sale because an insider may be on the other side. For small stocks, these expected losses are still only 33 cents on a $10,000 transaction. But in circles where this happy information is not widely known, investors with inflated perceptions of their disadvantage may still be reluctant to trade. Our findings should help to overcome their inhibitions.

The current regulatory system has two critical components, reporting requirements and the short-swing rule. The former, a minor clerical imposition, assures that information on insider trading comes out rather quickly, surely a virtue

[43] It is possible to relax the assumption of equal-weighted time periods by using a GLS procedure with weights proportional to the fraction of the overall market held by the insider portfolio. In untabulated tests using this technique, we find results quantitatively similar to those in tables 2 and 3. Thus, we find no evidence of higher profits when more value is traded. Of course, these GLS weights are from value-weighted trades, so we are not controlling for bunching under most filter rules.

if we think information disparities impede market function. The short-swing rule, which requires insiders to disgorge profits from any trade shorter than 6 months, imposes nontrivial liquidity and costs on insiders. Effectively being forced to hold a stock for 6 months reduces the number of trades that an insider can undertake with a given amount of capital, and requires them to accept the risk of holding a position even though it has progressed beyond their target level.

These costs constrain the volume of insiders' trades. However, the costs impose a deadweight loss. If we abandoned the short-swing rule, but imposed a tax on insider trades just equivalent to the costs they are now bearing, we might arrive at same level of trading, but have tax dollars to spend elsewhere. However, there is no obvious tax scheme—say a per-dollar of trade charge or a percentage of profits—that mimics the effects of the current rules.[44] Still, efforts to examine alternative constraining mechanisms seems desirable. For example, research that examined the volume and profitability of insider trading across tax regimes, either across states with different capital gains rates or across sufficient time to allow rates to change, could provide insights into the effects of an additional tax on insiders' profits.

The key policy question, beyond the choice of desirable regulatory instruments, is how constraining the system should be. Our principal accomplishment in this paper has been to quantify the tilt in the playing field enjoyed by insiders. Due to the disparity of numbers between insiders and outsiders, what appears as an easy downward slide for the insiders produces an imperceptible upward tilt for those who must trade against them. The question of fairness falls to the eye of the beholder. An answer to it would tell whether the current system should be tightened or loosened.

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[44] If we abandoned the short-swing rule in favor of a percentage-of-profits tax, presumably insiders would undertake any trade offering nontrivial expected positive value. Today's regulations, by contrast, induce insiders to only make trades with high expected profits, lest more attractive trades come along.

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## APPENDIX A

### Data Issues

Form 4 must be filed with the SEC within 10 days following the end of each month in which there is a change in direct or indirect insider ownership. Among the information required on Form 4 are: name and address of reporting person, issuer name and ticker or trading symbol, relationship of reporting person to the issuer (officer, director, or the like), filing date, type of security traded, transaction date (month/day/year), transaction code (for example, open-market transaction, private transaction, transaction under an employee stock ownership plan), number of equity securities traded, per-share price of equity securities, ownership form (direct or indirect).[45]

We restrict our study to open-market transactions in equity securities that have data available from the Center for Research in Securities Prices (CRSP). Over the sample period January 1, 1975 to May 31, 1996, there were 897,495 open-market transactions (385,025 purchases and 512,470 sales).[46] Of this number, 17,340 (1.9%) have missing transaction dates, leaving 880,155. We next purged duplicate transactions (those with identical data in all categories) from our sample. We believe these duplicates can occur for many innocuous reasons. This step removes 56,909 (6.5%) and leaves 823,246.

Prior to May 1991, Form 4 distinguished between open-market purchases and sales (transaction codes P and S) and private transactions (transaction codes J and K). During this period, open-market transactions outnumber private transactions by a ratio of about 11 to 1. After May 1991, private transactions use the same codes as open-market transactions. Ideally, we would exclude private transactions from our database: these transactions may take place with restricted securities, the counterparty often knows he is trading with an insider, and the trade is much more likely to be executed for liquidity or diversification motives than are open-market transactions. Therefore, we do not include any private transactions prior to May 1991, and we use several filter rules, discussed below, to eliminate the largest private transactions after that date. These same filter rules also purge the data of obvious coding errors.

Our first filter removes all transactions where the shares traded exceed trading volume for that day. Since private transactions would not be included in the exchange-traded volume of the day, this filter is likely to catch many of the largest post-1991 private transactions. This eliminates 4,018 transactions (0.5%) and leaves us with 819,228. Our second filter purges all transactions whose prices fall outside the daily trading range reported on CRSP. We call these *bad prices.* There are many reasons that bad prices can occur: a private transaction may be executed outside of the range; the date, price, or transaction type may be miscoded by the insider; input errors may be made by the data provider; and so on. The frequency of these problems, given below, is high enough to dissuade us from using the reported transaction prices in our analysis. Furthermore, most of the reasons given for bad prices would also render the transaction unsuitable for inclusion in the purchase and sale portfolios, even using the closing prices.

Our analysis suggests that the majority of transactions with bad prices are due to misreports or miscodes of the date (either by the insider or the data provider). Our procedure necessitates that we first purge all transactions where CRSP provides no information on the trading range. This results in a loss of 35,229 transactions (4.3%). Of the remaining 783,999 transactions, 225,770 (28.8%) have bad prices. To see how many of these may be due to simple miscodes of the date (perhaps because the filing date is miscoded as the trading date), we calculate a trading range beginning on the first day of the previous month and extending until the last day of the current month. Out of 225,770 trades with bad prices, 166,392 (73.7%) fall within this extended trading range. The remaining 59,378 trades with bad prices are likely to be private transactions not caught in the previous filter, and other miscodes by the insider or the data provider. Our final data set includes 558,229 transactions (208,055 purchases and 350,174 sales).

These filters could not catch all possible errors in the data. For example, any miscoded dates that do not have bad prices will remain in the data set. Since such trades must necessarily be in stocks with small price changes around the transactions, they are likely to bias our abnormal returns toward zero. Our diagnostic tests suggest that the value-weighted fraction of such bad trades is likely to be small and should not cause qualitative changes in our results. Similarly, some private transactions will escape the filters. Since our filters would have caught about 72% of the private transactions before May 1991, and the ratio of private transactions to open-market transactions is small, we doubt that eliminating the remaining private transactions would qualitatively change the results.

## APPENDIX B

### The Characteristic-Selectivity (CS) Measure

This appendix details the computation of the CS measure described in section III. This measure is based on the methodology of Daniel et al. (1997). For each insider transaction portfolio, the monthly measure of abnormal returns is calculated as the return on a zero-investment portfolio that is long in the insider transaction portfolio and short in a portfolio constructed using equivalent weights in the matching bins. In effect, this just combines the monthly abnormal returns for each stock in the portfolio.

The assumption underlying this model is that all stocks in the same bin have exactly the same expected return. If this assumption is satisfied, then the performance measure will have a zero expected return at all times. Thus, the insider portfolios that shift their portfolio composition conditional on expected factor realizations will have no bias in their estimated performance measure.

A more formal description of the methodology is:

$d \in t$: the set of all days $d$ in month $t$,

[45] Goodman (1991).

[46] For transaction dates after May 1991, there are also some private transactions in our data set. Our methods for disentangling these trades from open-market transactions are discussed below.

$s \in i$: the set of all stocks $s$ held by portfolio $i$,
$b(s)$: bin $b$ matched to stock $s$,
$R_{s,d}$ = net return for stock $s$ on day $d$,
$R_{b(s),d}$ = net return for bin $b$ matched to stock $s$ on day $d$, and
$W_{s(i),d}$ = weight placed on stock $s$ by portfolio $i$ on day $d$.

Using this notation, the CS measure for each month, $CS_{i,t}$, is then calculated as

$$CS_{i,t} = \prod_{d \in t} \left(1 + \sum_{s \in i} W_{s(i),d} R_{s,d}\right) - \prod_{d \in t} \left(1 + \sum_{s \in i} W_{s(i),d} R_{b(s),d}\right), \qquad \text{(B-1)}$$

where $\sum_{s \in i} W_{s(i),d} R_{s,d}$ is the actual net return for portfolio $i$ on day $d$, and $\sum_{s \in i} (W_{s(i),d} R_{b(s),d})$ is the net return that would be achieved on day $d$ if all funds were invested in the matching bins. The measure $CS_i$ [equation (3)] is then calculated as the mean of the monthly measures $CS_{i,t}$.

Not all stocks will be included in the CS calculation; if a stock cannot be matched to a bin, then it is not included in the test. The two main reasons for a failure to match are, first, insufficient past returns for a momentum calculation and, second, the absence of a book-equity observation in COMPUSTAT. Both of these data requirements lead to new issues being deleted from the portfolios. To the extent that new issues underperform similar stocks, this causes an upward bias in the estimated selectivity performance measure.[47] If such an upward bias exists, it does not seem to have a significant effect on the results. For example, when we repeat the CAPM and four-factor tests of table 1 using returns calculated only from stocks that have bin assignments, then the results are quite similar: the CAPM $\alpha$ is 55 basis points for purchases (13 basis points lower than the corresponding $\alpha$ of 68 basis points in table 1) and $-16$ basis points for sales (only one basis point higher than the corresponding $\alpha$ of $-17$ basis points in table 1); the four-factor $\alpha$ is 44 basis points for purchases (8 basis points lower than the corresponding $\alpha$ of 52 basis points in table 1) and $-1$ basis points for sales (4 basis points higher than the corresponding $\alpha$ of $-5$ basis points in table 1).

[47] See Loughran and Ritter (1995) and Brav and Gompers (1997) for evidence on the new-issues bias. On a bin-adjusted basis, Brav and Gompers's (1997) work suggests that this bias should not be large. See also Chan, Jegadeesh, and Lakonishok (1995) for a discussion of the bias induced by omitting stocks that do not have data in COMPUSTAT.