

# Can Traders Beat the Market? Evidence from Insider Trades

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## **Abstract**

Using the comprehensive trading data for the U.S. corporate insiders between 1993 and 2008, we document robust evidence that insiders as a whole achieve transaction prices superior to the volume-weighted average prices. This outperformance, expressed as a positive trading alpha, remains after we control for trade difficulty, insider reputation and the corporate role ranks of insiders. Upon analyzing the time series patterns of portfolio returns to strategies of mimicking corporate insiders with abnormal trading alphas in the extreme quartiles, we conclude that the outperforming insiders at the aggregate level resemble value investors who act on long-term fundamental information, trade patiently and earn rents from providing liquidity. Moreover, outside investors benefit from mimicking the acts of outperforming insiders in real time. The sizeable profit from this mimicking strategy withstands the erosion from adjustments for standard factors in the asset pricing literature and the adjustment for stock characteristics.

*JEL Classifications:* G10, G14

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# 1 Introduction

Performance evaluation is critical to the function of any competitive business, and the question as to whether money managers are able to “beat the market” has long been controversial in the investment literature due to the debate over market efficiency. Somewhat surprisingly, there has been little study examining a related question, i.e., whether or not traders outperform the market in terms of managing transaction costs. In this paper, we set out to evaluate the performance of U.S. corporate insiders in the context of transaction costs and uncover empirical evidence of insiders obtaining better than market average prices. Moreover, it appears quite profitable for outside investors to identify those insiders who have superior trading performance and mimic their trades in real time.

As insiders place their orders, those transactions can potentially move the price in the direction of their orders, resulting in a price impact that can be interpreted as the deviation of the transaction price from the fundamental price in the absence of insider trades. To the extent that market makers interpret orders from insiders as motivated by value-relevant information, the insider trades coincide with a positive price impact. In this paper, we follow Berkowitz et al. (1988) and use the volume-weighted average prices (VWAP) on the trade day as the benchmark against which to compare insider transaction prices after carefully removing the effect of insider trades from the benchmark. Hence, a negative price impact for an insider order (i.e., buy at a price lower than the VWAP or sell at a price higher than the VWAP) reflects the price improvement that the insider obtains relative to the daily benchmark. For this reason, we label the price improvement as “trading alpha.”

Using the comprehensive insider trading data in the U.S. between 1993 and 2008, we find that corporate insiders as a group have an average raw trading alpha of 4.2 cents for purchases and 3.6 cents for sales, both of which are reliably positive. The abnormal trading alpha amounts to around 10 cents per share for both insider purchases and sales, which is statistically significant at the 1% level, after we control for trade difficulty, insider reputation and their corporate role ranks. We interpret this finding as evidence of insiders beating the market in that they are indeed able to obtain favorable transaction prices relative to the volume-weighted average prices.

It is plausible to attribute the insider outperformance at the aggregate level to skill or style. The positive abnormal trading alpha can represent the trading skill of insiders or brokers in terms of delivering superior execution quality. Alternatively, it can also reflect the investment style of insiders who earn liquidity rents from submitting passive orders. To run a horse race between these two interpretations though, it requires more detail than what the U.S. insider trading data would allow. For instance, it is necessary to track the identities of brokers hired by the insiders and differentiate the investment styles among insiders and their brokers. The type of insider orders and the venue of insider trades can also affect

the transaction costs. Unfortunately, however, the existing regulations governing the insider trades do not mandate the disclosure of these details. Therefore, it is difficult to directly test the skill interpretation against the style interpretation for the insider outperformance in managing transaction costs.

This paper makes a novel contribution to the literature by indirectly disentangling the trading skill interpretation from the investment style interpretation through the time-series pattern of portfolio returns to strategies mimicking the insiders. The separation is possible here because the investment style interpretation hinges upon the distinction between short-lived information and long-term information whereas the trading skill interpretation makes no such distinction. Specifically, trading based on short-lived information is one defining characteristic of traders who consistently demand immediacy and thus incur negative abnormal trading alpha. In contrast, those who trade on long-term information would provide liquidity and enjoy positive abnormal trading alpha. To take advantage of this distinction, we extend the investment style argument in Keim and Madhavan (1997) and reach two empirical predictions. First, mimicking the actions of insiders with extremely negative abnormal trading alpha should be profitable in the short term but the long term profitability may attenuate or reverse. Second, mimicking the actions of insiders with extremely positive abnormal trading alpha should be profitable in the long term. In contrast to the predicted diverging profit patterns under the investment style interpretation, the trading skill interpretation predicts a lack of discernible profit pattern for the mimicking strategies because the trading skill has nothing to do with the information content of the trades or the life cycle of the underlying information.

Based on the U.S. corporate insider trades, we demonstrate evidence that mimicking the purchases of insiders with extremely positive abnormal trading alpha delivers a profit that more than doubles the profit from mimicking the purchases of insiders with extremely negative abnormal trading alpha for the first month following the portfolio formation. Over the twelve-month holding period, it pays off to mimic those insiders with extremely positive abnormal trading alpha. Mimicking those insiders with extremely negative abnormal trading alpha, on the other hand, pays off only in the short term and suffers attenuating profits and even losses in the long term. Therefore, the profitability patterns of mimicking strategies in our sample are consistent with the two predictions under the investment style interpretation. We interpret these findings as evidence in favor of the investment style interpretation rather than the trading skill interpretation.

Our paper is quite unique in that it naturally bridges the transaction costs literature with the insider trading literature on the foundation of differences in investment style advocated by Keim and Madhavan (1997). Our trading alpha metric certainly stems from the empirical literature on transaction costs.<sup>1</sup> A number of studies have utilized proprietary data to analyze

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<sup>1</sup>The empirical literature of transaction costs is voluminous. An incomplete list of some early work includes

the different components of transaction costs for institutional investors.<sup>2</sup> This paper focuses on the price impact as one component of implicit costs for corporate insiders as opposed to institutional investors. It is well documented in the literature (e.g., Keim and Madhavan, 1998) that implicit costs dominate explicit costs in magnitude. The price impact is arguably the most important and measurable part of transaction costs in the context of insider trading. In fact, it is empirically infeasible to consider other components of costs for insider trades.<sup>3</sup> There are several unique advantages in focusing on corporate insiders as opposed to institutional investors. First, the insider trading data are directly obtained from the reports that insiders file with the SEC and thus are more likely to be order-level data rather than trade-level data. Chan and Lakonishok (1995) and Keim and Madhavan (1998) stress the importance of setting the unit of observation at the order level and assess the price impact associated with the entire package of trades in each order as opposed to individual trades. The insider trading data satisfy this requirement. Second, the insider trading data clearly mark the identity of traders per regulatory requirement and thus make it feasible to study the reputation track record that insiders accumulate over time in the context of transaction costs. Third, some studies use the prices or quotes around the transaction as the benchmark price to measure price impact, but the insider trading data lack the detailed time stamp within the day. Using the daily VWAP as the benchmark bypasses this problem. Moreover, the VWAP benchmark makes the trading alpha a natural barometer of whether traders beat the market. Finally, prior literature mainly uses proprietary data of institutional trades for a relative short time period when studying the transaction costs, whereas the insider trading data in this paper are publicly available for a longer period of time.

One contribution of this paper to the transaction costs literature is the new finding that corporate insiders as a group are able to obtain favorable transaction prices. We are also able to further develop the investment style argument in Keim and Madhavan (1997) and hypothesize different time-series patterns of profitability between traders who exploit short-lived information and those that trade on long-term information. The U.S. corporate insider trading data support these predictions and provide corroborative evidence for the investment

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Beebower and Priest (1980), Berkowitz et al. (1988), Arnott and Wagner (1990), Collins and Fabozzi (1991) and Wagner and Banks (1992). Note that trading costs are usually decomposed into explicit costs and implicit costs. Given the lack of reporting for implicit costs, there is considerable disagreement in the literature over how to best measure implicit costs. There also are a number of recent studies that analyze the transaction costs for institutional investors, including Chan and Lakonishok (1995), Keim and Madhavan (1997), Jones and Lipson (2001), Conrad et al. (2001, 2003), Chiyachantana et al. (2004), Goldstein et al. (2009) and Anand et al. (2009).

<sup>2</sup>Keim and Madhavan (1997) emphasize the role of investment style in determining the total costs. Goldstein et al. (2009) focus on the commissions (a component of explicit costs) and analyze the institutional trading patterns in response to the rigid structure of commissions. Anand et al. (2009) study the opportunity cost of non-execution (also known as “implementation shortfall”, a component of implicit costs) and document the performance persistence of certain institutional trading desks.

<sup>3</sup>For instance, the insiders are not required to report explicit costs such as commissions and taxes when filing with the SEC. Similarly, insiders are not obligated to report the timing details of their decisions, resulting in the difficulty of measuring the implementation shortfall as an opportunity cost.

style interpretation for the insider outperformance mentioned earlier.

This paper is also naturally related to the insider trading literature (see Seyhun, 1998, and Jeng et al., 2003, for a survey of the literature). Specifically, one branch of the insider trading literature applies various intensity rules to filter useful signals from insider trades.<sup>4</sup> For instance, Cohen et al. (2009) classify insiders into routine traders and opportunistic traders based on the timing pattern of past insider trades and document the success of following those opportunistic traders. This paper marks an important departure from that literature because the trading strategies here essentially pick stocks based on the insider abnormal trading alpha, which is rooted in the analysis of transaction costs. We also confirm the common finding in the literature (e.g., Lakonishok and Lee, 2001; Jeng et al., 2003) that mimicking insiders on the buy side is profitable over the short term but there is much weaker potential from imitating the insider sales. We further contribute to the literature by demonstrating that it is highly profitable to mimic the group of insiders with extremely positive abnormal trading alpha. Given monthly portfolio rebalancing, the long-short strategy generates an annualized return of 18.24% under the equal-weighting scheme (or 14.76% under the value-weighting scheme) and the profit remains positive and statistically significant even after we adjust for standard models of factor pricing and after we use the characteristic-selectivity approach in Daniel et al. (1997).

The balance of the paper proceeds as follows. Section 2 describes the data and methodology of constructing the primary variable of interest in this paper. In Section 3 we carry out the regression analysis of the trading alpha, controlling for trade difficulty, insider role ranks and reputation measures. Section 4 analyzes the profitability of trading strategies for outside investors to mimic insider trades in real time that pick stocks solely based on the insider abnormal trading alpha. We conclude in Section 5.

## 2 Data and Methodology

### 2.1 Insider Trades

Our primary data source is Thomson Reuters Insider Filing Data Feed, which provides a historical archive for the transactions of persons subject to the disclosure requirements of Section 16(a) of the Securities and Exchange Act of 1934. Corporate insiders are legally defined to be corporate officers, directors and large shareholders who own more than 10 percent of the respective company's stock. If insiders buy or sell their firm's stock, they are mandated to file with the Securities and Exchanges Commission (SEC) within 10 days after the end of the month in which they traded. Starting from August 29, 2002, insiders are

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<sup>4</sup>See Jeng et al. (2003) and Cohen et al. (2009) for a survey of this literature and the references therein.

required to report their trades within two business days. As is typically done in the insider trading literature, we focus on Form 4 data that provide the following information: the name and address of reporting person, issuer name and trading symbol of the security, relationship of reporting person to the issuer (officers, directors or other positions held by the reporting persons in issuers), whether it is a purchase or sale, transaction date, price and trade size in shares.<sup>5</sup>

As documented in Appendix A of Jeng et al. (2003), this database contains a number of data errors due to either reporting mistakes or data transcribing issues. We employ a number of filters to mitigate the problem. For an insider trade to stay in our sample, the underlying stock must have data coverage by the Center for Research in Security Prices (CRSP), from which we obtain the time series of stock returns, market equity and other firm characteristics. We focus only on open market transactions of equity securities. The reported trades cannot have a transaction price outside the daily price range as recorded in CRSP on the trade day. We further restrict that transaction prices fall between \$5 and \$500 and each transaction shall involve at least 100 shares but no more than the daily trading volume recorded in CRSP. The final sample spans between 1993 and 2008, coinciding with the inception year of the New York Stock Exchange Trades and Quotes (TAQ) database that we rely on to implement the trading alpha metric (discussed below).

Tables 1 and 2 provide the annual summary statistics of insider trades. It is clear that insider trades have become much more widespread and pervasive over the 16-year sample period. For instance, the number of insiders who report purchases (sales) increases from 225 (480) in 1993 to 6,462 (10,048) in 2008. There are insider trades for nearly every trading day of the year. The number of trades, share volume and dollar volume totaled more than 2.2 million trades, 18 billion shares and 590 billion dollars, respectively, over this sample period. These patterns speak to the growing importance of insider trades and motivate us to examine how well these insider trades were executed. Note that insider sales are much more prevalent than insider purchases during this period. Insider sales account for 86% of aggregate insider trades in terms of the number of trades. When measured in total share volume and total dollar volume, the fraction of insider sales of all insider transactions is 85% and 92%, respectively. The dominance of insider sales can be partially attributed to the increased use of stock option awards and grants that are designed to incentivize corporate insiders and align their interests with those of other shareholders. Corporate insiders often execute these option awards and grants, which are not part of our sample, and then sell their shares in the open market, which are part of our sample. As net sellers on average, the corporate insiders may also sell their company stocks for diversification and liquidity purposes.

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<sup>5</sup>A sample SEC Form 4 can be obtained from [www.sec.gov/about/forms/form4.pdf](http://www.sec.gov/about/forms/form4.pdf).

## 2.2 Trading Alpha

The transaction costs literature has provided numerous cost measures with varying areas of focus. The insider trading data make it possible to study the price impact, an implicit cost component of total transaction costs, but not other components. For instance, insiders are not compelled to disclose the explicit costs such as commissions and taxes paid when filing reports with the SEC. We also rule out studying spread measures here due to the lack of precise time stamp for insider trades. Moreover, in the context of insider trading it is difficult to measure the opportunity costs of execution failure (also known as implementation shortfall) because insiders disclose the date of trade but not the time when they first decided to trade.<sup>6</sup> Though the price impact represents an incomplete picture of total transaction costs, there is a consensus in the literature (e.g., Keim and Madhavan, 1998) that implicit costs dominate explicit costs.

To measure the price impact, the transaction prices can be compared to various benchmark prices in the existing literature. In this paper, we follow Berkowitz et al. (1988) and use the volume-weighted average prices (VWAP) as the benchmark. Over time the VWAP measure has become the standard benchmark for evaluating the execution quality of professional traders.<sup>7</sup> Using the daily VWAP as the benchmark, a negative price impact for an insider order (i.e., buy at a price lower than the VWAP or sell at a price higher than the VWAP) reflects the price improvement that the insider obtains relative to the daily benchmark. For this reason, we label the price improvement as “trading alpha.” The trading alpha is analogous to the abnormal return in excess of the benchmark factors in investment performance evaluation that is known as “Jensen’s alpha.” A positive trading alpha can then be interpreted as evidence of traders beating the market average prices. It is useful to distinguish the implicit costs of insider purchases from those of insider sales so we construct two separate VWAP series. Specifically, we classify each trade from NYSE Trade and Quote (TAQ) database into buyer-initiated and seller-initiated trades using the Lee and Ready (1991) algorithm that is standard in the literature.<sup>8</sup> All the prices for buyer-initiated trades are weighted by their respective size on a given day for a given stock, and the daily sum becomes the VWAP on the buy side. The VWAP on the sell side can be constructed in a similar way.

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<sup>6</sup>Perold (1988) popularizes the notion of implementation shortfall, which is defined as the difference between the market price at the decision time and the eventual transaction price.

<sup>7</sup>Madhavan (2002) provides a survey about various versions of VWAP and their usefulness in trading strategies (also known as the VWAP strategies) and performance evaluation (the VWAP benchmark). Hu (2007) argues that the VWAP to trade execution essentially amounts to the market index return to investment performance.

<sup>8</sup>Lee and Ready (1991) algorithm compares the trade price with the prevailing quote price. A trade is classified as buyer-initiated (seller-initiated) trade if the trade price is greater than (less than) the mid-point of the prevailing quote. For trades that have a transaction price identical to the mid-point of prevailing quote price, the tick test is used. That is, a trade is a buyer-initiated (seller-initiated) trade if the trade price goes up (down) from the last trade. Trades are not classified and discarded if the trade price doesn’t change from the last trade.



Having outlined the procedure to calculate the VWAP, we define the trading alpha as

$$TrdAlpha = (2 \cdot isbuy - 1) \cdot (VWAP - tprice),$$

where *isbuy* is an indicator taking the value of 1 for insider purchases and 0 otherwise; and *tprice* is the reported transaction price of insider trades. Even though the trading alpha is defined as the price differential in dollars throughout the paper, we also carry out all the analyses expressing the trading alpha as a percentage of the transaction price. The qualitative nature of the results under the alternative specification remains unaltered so we report only the results with trading alpha in dollars to conserve space.

Our trading alpha measure differs from the implicit cost measure in Keim and Madhavan (1998). For buyer-initiated orders, they compute the ratio of the volume-weighted average prices of various component trades in each order to the closing price on the day before the trade decision, and define the implicit cost as the ratio in excess of 1. The implicit trade cost for a seller-initiated order carries an opposite sign to this price change. The main difference between our trading alpha and their implicit cost measure is the choice of the benchmark price. Keim and Madhavan (1998) use the closing price on the day before the trade decision as the benchmark price whereas we use the VWAP in the same day as our benchmark price. This difference in design mainly stems from the difference in research goals. Since we are more interested in whether insiders as a whole can beat the market average prices when they trade and are less concerned with the true decision price for insiders, the VWAP is a more appropriate benchmark than the closing price on the previous day.

One problem with using the VWAP as a benchmark is that the construction of VWAP series includes the insiders' own trades. Hu (2009) discusses the bias in VWAP when traders' own trades are not excluded. This bias turns out to be a function of traders' own trades as a fraction of the total trading volume, and thus it can be substantial for traders that dominate the volume in certain stocks. Given that insider trading volume in many cases is a significant portion of the total trading volume, it is important to address this bias. We adopt the approach in Hu (2009) to correct this bias in two steps. First, we divide the volume of insider trades by the daily trading volume to obtain the fraction of insider trades, denoted by  $f$  in Hu (2009). We then calculate the revised VWAP by multiplying the untreated VWAP by the adjustment factor of  $1/(1 - f)$ .

Table 3 presents the summary statistics of the trading alpha separately for insider purchases and sales. Panel A shows that on average insiders achieve a trading alpha of 4.2 (3.6) cents when they buy (sell). In our sample, there are both insiders who get prices inferior to the VWAP and insiders who get prices superior to the VWAP, but the latter group dominates at the aggregate level. The median of raw trading alpha is 2 cents for both insider purchases and sales. Both the means and medians are statistically significantly different from zero. We

have purged all observations with raw trading alpha beyond the tail 1% on both ends to mitigate the concern about outliers. To assess the economic significance of the raw trading alpha, note that insiders have sold more than 15 billion shares over the sample period. An average raw trading alpha of 3.6 cents for insider sales easily translates to the cost savings of 54 million dollars in total, which is a sizeable sum.

In one robustness check, we slice the full sample into four sub-samples, with four years apiece, and report the summary statistics in Panels B through E. The basic conclusion of a positive and significant raw trading alpha for both insider purchases and sales holds for each sub-sample. A few time-series patterns emerge from the sub-period analysis. It is clear that the insider trades have gone up substantially over time both for purchases and sales. What is also apparent is the fact that insiders have higher raw trading alpha in the first half of the sample than in the second half. The declining raw trading alpha in the second half coincides with the period following the decimalization in the U.S. stock markets in 2001, after which the equity transaction costs have come down sharply. Even though in the full sample insider purchases are associated with higher raw trading alpha than insider sales, this is not always the case in sub-samples.

Taken together, Table 3 suggests that on average insiders achieve positive trading alpha on both purchases and sales of stocks. This trading alpha is both economically and statistically significant. A series of questions arises naturally. What are the main determinants of trading alpha? Can this positive trading alpha be explained away by trade difficulty and insider characteristics? In the next section, we attempt to address these and other questions.

### 3 Regression Analysis of Trading Alpha

Transaction costs can certainly be related to the complexity of the trading environment, so it is important to examine if the insider trading alpha is solely determined by trade difficulty. We start with a few well-established basic measures of trade difficulty and then use extended measures of trade difficulty. To further explain the cross-sectional and time-series variation of the trading alpha adjusted for trade difficulty, we allow for a number of insider characteristics that are measurable and have available data.

#### 3.1 Basic Model of Trade Difficulty

It has long been recognized that transaction costs are directly related to the difficulty of executing a trade. As is typically done in the literature, we run a multivariate regression with a few basic proxies for trade difficulty,

$$TrdAlpha = \alpha_0 + \beta_1 \cdot shares + \beta_2 \cdot mktcap + \beta_3 \cdot tprice + \varepsilon.$$

Among the explanatory variables, *shares* denotes the insider choice of share volume, *mktcap* stands for the logarithmic market equity of the firm with which the insider is affiliated, and *tprice* is the transaction price that the insider obtains. All variables are measured contemporaneously except the market equity in the preceding month.

The intercept  $\alpha_0$  captures the average abnormal trading alpha after adjusting for trade difficulty. Larger orders should imply a higher price impact and thus a lower trading alpha, so we expect  $\beta_1$  to be less than zero. The market capitalization is included as a proxy for liquidity, and its effect on trading alpha depends on the trader’s role. Providing liquidity in a small and thus illiquid stock can be costly, so the liquidity provider would demand a high rent (i.e., a positive trading alpha), resulting in a negative relationship between the market capitalization and the trading alpha. Similarly, demanding liquidity in a small stock requires high payment (i.e., a negative trading alpha), and thus we expect a positive relationship between the market capitalization and the trading alpha. In short, we hypothesize  $\beta_2$  to be less than zero among traders who supply liquidity and  $\beta_2$  to be greater than zero among those who demand liquidity. The share price is included because the dependent variable is measured as a price differential (i.e., improvement over the volume-weighted average price) and thus can be proportional to the share price. For similar reasons, Goldstein et al. (2009) include the share price as a determinant for commission per share, and other studies include the reciprocal of share price as a determinant of transaction costs when transaction costs are measured as a percentage of price.<sup>9</sup> We expect a positive  $\beta_3$  among liquidity suppliers and a negative  $\beta_3$  among liquidity demanders.

We carry out the regression analysis using both the pooling regression and Fama-MacBeth regression methods and opt to report the more conservative results from the latter approach. Specifically, we estimate the regression for each month between 1993 and 2008 using the entire cross-section of corporate insider trades in the U.S. The time series averages of parameter estimates are then used to gauge the statistical significance of the explanatory variables as well as the intercept. Note that the insider purchases are estimated separately from the insider sales. In addition to the regression using all purchases or sales, we also estimate the regression for records with positive trading alpha separately from the regression for those with negative trading alpha. The separation by the sign of trading alpha is designed to capture possible differences related to the insider role in the process of liquidity provision. For ease of interpretation, we label insiders with a positive trading alpha as “liquidity suppliers” and insiders with a negative trading alpha “liquidity demanders.”

Table 4 presents the regression results for the model with basic measures of trade difficulty. All the predicted signs are supported by estimates that are statistically significant while the

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<sup>9</sup>We have also carried out all the analysis using a measure of trading alpha defined as the price improvement relative to the daily VWAP as a percentage of the transaction price. The results based on trading alpha in dollars remain qualitatively the same as the results based on trading alpha in percentage. For brevity we report only the former set of results.

estimated coefficients with a wrong sign are invariably insignificantly different from zero. The share price is strongly significant with the predicted sign in all six regressions. The firm size is nearly as strong a predictor, with the only exception being the regression among liquidity demanders. The insider choice of share volume is rather weak especially when explaining the trading alpha among insider purchases. Interestingly, insiders who are perceived to be providing liquidity enjoy the average rent of about 36 cents per share on purchases and 44 cents per share on sales, while those demanding liquidity incur the average payment of about 3 cents per share on purchases and 22 cents per share on sales, after adjusting for rudimentary measures of trade difficulty.

Given the dominance of records with positive trading alpha in this sample, we find an average alpha of about 20 cents per share among purchases and 11 cents per share among sales after controlling for trade difficulty when all insider trades are estimated jointly without distinguishing the sign of trading alpha. The evidence in this sample indicates that insiders act as liquidity providers on average and earn rents accordingly. This result supports the finding in Chan and Lakonishok (1995) and Keim and Madhavan (1997) that value investors incur a negative price impact in their sales. Not surprisingly, the estimated coefficients under the joint estimation carry the same set of signs as in the regression among liquidity providers.

The adjusted  $R^2$  under the joint estimation is dramatically lower than the two regressions separated by the sign of the raw trading alpha, reflecting the general difficulty with disentangling orders that demand liquidity from those that provide liquidity ex ante, and the complexity with identifying proxies for trade difficulty with readily available data. Nevertheless, the relatively low adjusted  $R^2$  under the joint estimation is not unique to our sample and in fact is often present in the literature concerning the transaction costs of institutional investors.

### 3.2 Extended Model of Trade Difficulty

Having presented the results for a basic model of trade difficulty, we now expand the group of proxies for trade difficulty to include daily stock return, stock volatility (measured as the absolute daily return on the trade day) as well as an indicator variable that takes the value of 1 for stocks listed on the New York Stock Exchange (NYSE) and takes the value of 0 otherwise. The expanded regression design is

$$TrdAlpha = \alpha_0 + \beta_1 \cdot shares + \beta_2 \cdot mktcap + \beta_3 \cdot tprice + \beta_4 \cdot return + \beta_5 \cdot volatility + \beta_6 \cdot isnyse + \varepsilon.$$

From the perspective of a trader, it is more difficult to execute a buy (or sell) order on a day coinciding with a positive (or negative) return. Similarly, a stock with a higher level of volatility or a stock that is listed in an exchange other than the NYSE is often considered to exist in a more difficult trading environment. In such instances, liquidity providers would

charge more rents while those who demand liquidity have to pay more rents. In other words, we expect positive  $\beta_4$  among purchases from insiders who provide liquidity and sales from insiders who demand liquidity. A negative  $\beta_4$  should apply among purchases from insiders who demand liquidity and sales from insiders who provide liquidity. We also expect positive  $\beta_5$  and negative  $\beta_6$  among liquidity suppliers and the opposite signs among liquidity demanders. Given the dominant presence of insiders who are perceived to provide liquidity in this sample, the expected pattern of signs for the regression using all insider trades is:  $\beta_1 < 0$ ,  $\beta_2 < 0$ ,  $\beta_3 > 0$ ,  $\beta_5 > 0$  and  $\beta_6 < 0$  for both insider purchases and sales;  $\beta_4 > 0$  for insider purchases and  $\beta_4 < 0$  for insider sales.

We slice the sample into four pieces based on the insider role of liquidity provision and the trade initiation. Three important determinants for trading alpha emerge from the results in Table 5 for the extended model. The share price, the stock volatility and the indicator for NYSE have the predicted signs with strong statistical significance in all four sub-samples. Their influence on the transaction outcomes is very intuitive. Stocks with higher prices require higher liquidity rents in dollar, as would stocks with higher volatility. The distinction of market design is also important in that NYSE stocks appear to be associated with a lower liquidity rent. The other three measures of trade difficulty are weaker determinants for trading alpha, especially in the case of insider purchases and insiders who demand liquidity.

While it is useful to distinguish the insiders with positive raw trading alpha from those with negative alpha so as to capture the intuition behind the insider role in the liquidity provision process, this exercise can only be done ex post and it remains difficult to predict ex ante which orders would demand liquidity as opposed to supply liquidity. For this reason, in the remaining analysis we focus on the regressions with all insider purchases or sales regardless of the sign of the raw trading alpha. In the last set of columns in Table 5, with the sole exception for the NYSE indicator among sales, there is evidence that all measures of trade difficulty have the predicted sign and the vast majority of them are statistically significant.

A number of studies document the finding that buy orders appear to have higher price impact than sell orders. The observed price impact asymmetry is subsequently attributed to buy orders being more informative. Saar (2001) provides an excellent review of the literature. Chiyachantana et al. (2004) advance an intuitive explanation for the observed price impact asymmetry by linking the contemporaneous market condition to the price impact. They argue that liquidity suppliers charge higher rents for momentum orders (i.e., buy orders during a bullish market and sell orders during a bearish market) than contrarian orders (i.e., sell orders during a bullish market and buy orders during a bearish market). When using all insider trades, Table 5 shows a positive contemporaneous relationship between return and trading alpha among insider purchases and a negative one among insider sales. In other words, we witness positive  $\beta_4$  for insider purchases and negative  $\beta_4$  for insider sales just as

predicted. This is direct evidence confirming the intuition in Chiyachantana et al. (2004), even though insiders appear to earn rents from providing liquidity on average in this sample whereas institutional investors pay for demanding immediacy in their sample.

Compared to the base model of trade difficulty, the model with extended measures experiences substantial improvement in goodness of fit as measured by the markedly higher adjusted  $R^2$ . The estimated intercept, or the difficulty-adjusted trading alpha, averages about 10 cents for both insider purchases and sales, each of which is reliably different from zero. Again, there is evidence that insiders indeed beat the market on average and obtain a more favorable price than the volume-weighted average price even after controlling for trade difficulty.

### 3.3 Role of Insider Characteristics

The estimated model for trade difficulty helps to generate a time series, *AdjAlpha*, as the sum of the estimated common intercept in each month and the transaction-level residual. This series captures the portion of trading alpha that remains unexplained by various proxies for trade difficulty. To examine whether insider characteristics are able to explain the variations in difficulty-adjusted trading alpha, we run the following regression,

$$AdjAlpha = \alpha_0 + \gamma_1 \cdot isexecutive + \gamma_2 \cdot isofficer + \gamma_3 \cdot isfinexecutive + \gamma_4 \cdot reputation + v.$$

The insider trading data provide the role rank of insiders within their respective corporations, so we cast insiders into one of three categories: top executives, officers/directors and others. The dummy variable *isexecutive* takes the value of 1 for top executives and 0 otherwise. Similarly, the dummy variable *isofficer* takes the value of 1 for officers or directors and 0 otherwise. The dummy variable *isfinexecutive* takes the value of 1 for executives in the financial industry and 0 otherwise. While the insider trading literature has explored the implications of the information hierarchy on stock prices (e.g., Seyhun, 1986), we have no specific prior on how the insider role ranks might affect the trading alpha. The sign of the estimated coefficients for these dummy variables would reveal the trading performance of their respective group relative to all insiders that are non-executives and non-officers, which are presumably dominated by block holders.

Before discussing measures of reputation as part of the explanatory variables, we first recall the rather intuitive reputation hypothesis in Seppi (1990). Namely, traders who can credibly signal that their orders are liquidity motivated should incur little price impact by trading large blocks in the “upstairs market” where a block broker facilitates the trading by locating counterparties. This would in turn help these traders save transaction costs associated with a large price impact from the alternative strategy of placing a sequence of small trades in the “downstairs market.” Madhavan and Cheng (1997) test this reputation

hypothesis and find evidence of fairly small economic benefit for an average-size block trade to tap the upstairs market. They conclude that the main purpose of the upstairs market is to accommodate trades that may not otherwise occur. While the publicly available insider trading data do not indicate whether or not some insiders utilize the upstairs market or alternative trading systems to obtain superior execution prices, they do have one unique advantage. That is, the insider identity is revealed per regulatory requirements and thus empirical researchers are able to analyze the reputation track record that insiders accumulate over time in the context of transaction costs. In other words, we can test the influence of the reputation hypothesis on the transaction outcomes even in the absence of a clear identification of insiders' trading venue.

To test the reputation hypothesis, we design two proxies of insider reputation. For each insider we compute the daily volume-weighted trading alpha adjusted for trade difficulty, *AdjAlpha*. The first reputation measure for a given insider is the adjusted trading alpha for the same insider in the preceding day, which can be days or even months earlier depending on how frequently the insider trades. The rationale behind this measure is that an insider known for having provided liquidity before is likely to continue providing liquidity in the future. The second reputation measure builds on this idea and tallies the cumulative average adjusted trading alpha up to the trade day concerned. The reputation hypothesis posits that each of these reputation measures should be positively related to the trading alpha adjusted for trade difficulty, so we expect positive  $\gamma_4$ .

Based on regression results in Table 6 concerning various combinations of dummies for insider role ranks and reputation measures, there is clear evidence supporting the reputation hypothesis. Regardless of whether we use the short-term liquidity rent (or payment) or the long-term cumulative track record of liquidity rent (or payment), the insider reputation is positively related to the adjusted trading alpha and this positive association is strongly statistically significant. Those insiders who have earned liquidity rents in the past continue to earn positive adjusted trading alpha, and this pattern holds for both insider purchases and sales. In essence this insider reputation effect speaks to the persistence of adjusted trading alpha over time. As far as the role rank of corporate insiders is concerned, top executives appear to have lower adjusted trading alpha and there is little distinction between officers/directors and those non-executive-non-officer insiders. This pattern of results seems stronger among insider purchases rather than insider sales. One interpretation for this result is that corporate executives are less likely to credibly signal the lack of information motivation behind their orders. All else being equal, top executives in the financial industry enjoy higher adjusted trading alpha, likely reflecting the increased sophistication of these executives about financial transactions in general compared to insiders in other industries.

The evidence in this paper directly supporting the reputation hypothesis in Seppi (1990) marks an important contribution to the literature because it deepens our understanding of the

repeated interactions among traders as they inevitably influence the transaction outcomes. The finding here also opens a new window to the analysis of insider trades. Note however that there is still a large portion of variation for the abnormal trading alpha that cannot be explained by the insider characteristics for which we have available data. The average abnormal trading alpha, after controlling for trade difficulty and insider characteristics, is about 10 cents per share for both insider purchases and sales and is reliably different from zero.

## 4 Strategies on Abnormal Trading Alpha

Even though we have shown extensive evidence for the existence of positive abnormal trading alpha after adjusting for trade difficulty and insider-specific factors, we have not settled on the true source of the insider abnormal trading alpha. The positive abnormal trading alpha can be either a proxy for the trading skill of insiders or brokers in terms of delivering outstanding execution quality, or a measure of investment style much in the same way as value investors are able to earn liquidity rents. To shed light on the underlying source of insider outperformance, we allow outside investors to ride the coattail of insiders and evaluate the profitability of these mimicking strategies over time.

### 4.1 Sources of Insider Outperformance

The literature has documented supporting evidence that brokers play an important role in determining the execution costs for institutional traders. For instance, Conrad et al. (2001) find differences in execution cost among four types of brokers even after controlling for special situations attached to an order and the differences in institutions sending an order. Using a proprietary database of equity transactions by institutional investors, Anand et al. (2009) find that brokers exhibit significant heterogeneity in execution quality and that at least some brokers can deliver consistently better execution over time. Top brokers in their sample appear able to sustain their advantage over adjacent periods. They also show that institutional investors exert discretion in selecting brokers; that is, an institution's choice of a broker is sensitive to past execution performance. Taken together, there is evidence that brokers potentially play a role in contributing to the positive abnormal trading alpha.

The insider outperformance can also be related to the specific trading system used by insiders or their brokers. Conrad et al. (2003) show that in general lower trading costs can be achieved on alternative trading systems as compared to the costs of using traditional brokers. It is also possible that insider choices of trading venues contribute to their superior trading performance. Another source of the insider outperformance might be related to the commissions paid by insiders. While Berkowitz et al. (1988) find that there is no substitution



between commissions and implicit trading costs, Keim and Madhavan (1997) find that there exists a positive correlation between implicit and explicit costs. In other words, the explicit and implicit costs might be jointly determined.<sup>10</sup> We cannot rule out the possibility that insiders are paying very high commissions to their brokers and they are rewarded with superior trading performance in return.

Instead of attributing the outperformance to external factors such as broker skills, trading venue and broker commissions, Keim and Madhavan (1997) champion the notion that the investment style and order submission strategy complement trade difficulty in determining the transaction costs for institutional investors. They find that index managers and technical managers indeed incur higher total transaction costs than fundamental value managers, reflecting the idea that the former group of institutional investors is more likely to demand immediacy than the latter group. Rozeff and Zaman (1998) and Lakonishok and Lee (2001) document evidence that insiders are contrarian investors at the aggregate level. Thus one natural implication of this evidence is that those contrarian insiders supply liquidity at the time when liquidity rents are high, and thus should be able to achieve substantial savings on transaction costs. From this perspective, it is not surprising that insiders command a positive trading alpha on average before the contrarian strategy is taken into account. This finding is certainly consistent with the investment style argument in Keim and Madhavan (1997). Given the fact that insiders still deliver a positive trading alpha even after we control for their contrarian strategy through the inclusion of the same day return in addition to other measures of trade difficulty, it remains a challenge in how to best interpret the insider outperformance.

There is an active debate in the investment literature on whether a positive investment alpha should be attributed to the managerial skills and stock picking abilities of mutual fund managers, or attributed to the investment style that managers follow. Likewise, the advocates of the skill interpretation in the context of trading performance would credit the positive abnormal trading alpha to the skillfulness of insiders or their brokers in terms of delivering superior execution quality rather than to the investment style as emphasized by Keim and Madhavan (1997). To tease out which interpretation is favored by the data, we need to account for differences in investment style among insiders and their brokers. The trading aggressiveness of insiders or their brokers as well as the particular order types and trading venues used by insiders certainly can affect the outcome of transaction costs. Unfortunately, however, the insiders are not required to provide such information when filing the reports with the SEC. In the absence of such detailed data, it is difficult to directly disentangle the skill interpretation from the style interpretation.

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<sup>10</sup>One explanation they offer for the positive correlation is that the more difficult trades, which tend to have higher price impacts, are given to full-service brokers, who also charge higher commissions.

## 4.2 Separating Skill from Style

We now turn to the strategies of outside investors mimicking the insider trades in real time because the time series pattern of portfolio returns to such strategies can provide indirect evidence as to whether the skill interpretation or the style interpretation is better favored by the insider trading data. The gist of the trading strategy is to pick stocks based on the abnormal trading alpha of insiders. Before getting into the details of mimicking strategy, we need to develop a set of testable hypotheses that would help us distinguish the trading skill interpretation from the investment style interpretation for the insider outperformance.

According to Keim and Madhavan (1997), “Differences in investment style result in substantially different demands for immediacy of trade, and the resulting differences in order submission strategies likely cause differences in trading costs.” These authors present concrete examples to illustrate the contrast. Technical traders aim at capturing short-term price movements and thus have a strong demand for immediacy which leads to higher transaction costs. On the other hand, value traders are motivated by long-term fundamentals and can incur lower transaction costs due to more patient trading strategies. One key element of the investment style argument is the life cycle of information underlying observed trades. Trading based on short-lived information is one defining characteristic of traders who consistently demand liquidity and incur negative abnormal trading alpha. In contrast, those who trade on long-term information would provide liquidity and enjoy positive abnormal trading alpha.

Exploiting the different life cycles of information underlying the orders submitted by insiders with different levels of abnormal trading alpha, we extend Keim and Madhavan (1997) and reach two predictions for the investment style hypothesis. First, mimicking the actions of insiders with extremely negative abnormal trading alpha should be profitable in the short term but the long term profitability may attenuate or reverse. Second, mimicking the actions of insiders with extremely positive abnormal trading alpha should be profitable in the long term. Thus it is possible to empirically refute the investment style interpretation by examining the time series pattern of profitability from the mimicking strategy. To the extent that the abnormal trading alpha purely represents the trading skill of either insiders or their brokers, the contrast in trading skill should have nothing to do with the information content of the trades or the life-cycle of the underlying information. In other words, if the abnormal trading alpha truly reflects the trading skill, then it should be unprofitable for outsiders to mimic insiders and there should be no discernible difference in the time series pattern of profitability from mimicking insiders with very different levels of abnormal trading alpha.

In essence, the profitability analysis of a long-short trading strategy to mimic insiders sheds light on the true source of the abnormal trading alpha. This is possible because the investment style interpretation hinges upon the distinction between short-lived information and long-term information whereas the trading skill interpretation makes no such distinction.

### 4.3 Forecasting Stock Returns

We form and rebalance the mimicking portfolios at the end of each calendar month. The vast majority of insider trades in our sample were reported to the SEC on the day of trade. Given the timely disclosure of insider trades, it should be feasible for outside investors to observe the insider trades by the end of each month and form the mimicking portfolio in time. Carving out the part related to trade difficulty of the raw trading alpha, we are left with the adjusted trading alpha. For each corporate insider, we compute the volume-weighted daily adjusted trading alpha and then take the simple average for each month as the basis for ranking insiders within the month. The entire cross-section of insiders who traded in a given month is then sorted into four quartiles based on the level of insider abnormal trading alpha, and we assign the values for a set of four dummy variables indicating the presence of insiders of a certain type, or the lack thereof, for each firm month. Specifically, the dummy variable *ishighbuy* (or *ishighsell*) indicates the presence of any insider whose buy (or sell) order is associated with a positive abnormal trading alpha in the top quartile; the dummy variable *islowbuy* (or *islowsell*) indicates the presence of any insider whose buy (or sell) order is associated with a negative abnormal trading alpha in the bottom quartile. This exercise of sorting and ranking is done separately for insider purchases and sales.

Before describing our strategy of stock selection based on these four dummy variables, it is necessary to demonstrate that they are legitimate sorting devices to form a trading strategy. For this purpose, we run a set of regressions using the stock-specific monthly dummy variables, in conjunction with the logarithmic market equity *mktcap* and the book-to-market ratio *bmratio* in the preceding month as well as the last-twelve-month return *ltmret* over month  $t - 12$  and  $t - 1$ , to predict the one-month-ahead stock returns. That is,

$$\begin{aligned} \text{return}_{t+1} = & \phi_0 + \phi_1 \cdot \text{ishighbuy}_t + \phi_2 \cdot \text{islowbuy}_t + \phi_3 \cdot \text{ishighsell}_t + \phi_4 \cdot \text{islowsell}_t \\ & + \phi_5 \cdot \text{mktcap}_t + \phi_6 \cdot \text{bmratio}_t + \phi_7 \cdot \text{ltmret}_t + \eta. \end{aligned}$$

Table 7 presents the regression results. In the design with only two dummies indicating the presence of insider purchases, it is clear that stock returns are reliably higher in the month following insider purchases regardless of whether these insiders command extremely high abnormal trading alpha or extremely low abnormal trading alpha. Riding the coattail of insiders with positive abnormal trading alpha in the top quartile to buy the same stocks delivers a return of 1.15% in the next month. On the other hand, riding the coattail of those with negative abnormal trading alpha in the bottom quartile promises a return of 0.57%. It is fruitful to copycat selected insider purchases at least for the short term, but the return potential is halved by following the purchases of insiders with poor trading performance rather than those insiders with great trading performance. In the design with only two dummies indicating the presence of insider sales, the results exhibit the exact opposite signs. Insider

sales foretell the subsequent negative returns, and insiders who outperform have an effect that is twice as large as the effect among insiders who underperform, namely,  $-0.47\%$  versus  $-0.22\%$ .

These four dummies are indeed useful predictors for the one-month-ahead stock returns. It is valuable to mimic the actions of insiders with extreme levels of abnormal trading alpha, but much of the predictive power resides on the buy side, especially among the purchases from insiders who outperform. On the sell side, the magnitude of the return effect is much smaller in size and weaker in statistical significance. In fact, when all four dummies are competing against each other in the same regression, none of the sell-side dummies is significantly different from zero despite each carrying a negative sign. Controlling for the firm size, the book-to-market ratio and the last-twelve-month return does not change the quantitative pattern on the buy side by much. The sell-side effect associated with extremely negative alphas remains insignificant, although there is mixed evidence for the statistical significance of the sell-side effect with extremely positive alphas, depending upon the particular combination of firm-specific controls. The finding in this exercise that the buy-side effect dominates the sell-side effect is consistent with the extant literature of insider trading. For instance, Lakonishok and Lee (2001) find that insider purchases are informative while insider sales have no predictive ability for future returns. Jeng et al. (2003) report positive abnormal returns for insider purchases over a six-month period but insignificant abnormal returns for insider sales.

It is a very novel finding in this paper that mimicking the purchases of insiders who outperform in controlling transaction costs doubles the value of mimicking the purchases of insiders who underperform for the first month following the portfolio formation. That the difference in insider abnormal trading alpha on the buy side alone can drive a large return spread exploitable by outside investors erodes the credibility of the trading skill interpretation for insider abnormal trading alpha. Simply put, the trading skill of insiders or brokers in terms of execution quality should have nothing to do with the information content of insider trades, leading to a lack of return predictability for the dummy variables based on the insider abnormal trading alpha. The evidence here on the dummies capable of predicting one-month-ahead stock returns, therefore, does not support the trading skill interpretation and leans in favor of the investment style interpretation.

#### **4.4 Profitability Pattern of Mimicking Strategies**

To empirically test two earlier predictions regarding the time-series pattern of profitability for the investment style hypothesis, we form two trading strategies at the end of each month. The HBS strategy focuses on the actions of insiders who have positive abnormal trading alpha within the top quartile, buys stocks that these insiders bought and sells stocks that

they sold earlier in the month. The LBS strategy focuses on the actions of insiders who have negative abnormal trading alpha within the bottom quartile, buys stocks that these insiders bought and sells stocks that they sold. The investment on the buy side is worth \$1, as is the investment on the sell side. To mitigate noise arising from the rare occurrence of conflicting signals from different insiders from the same firm that traded in the same month, we exclude firm months in which there are both purchases and sales for the same stock from different insiders with abnormal trading alpha within the extreme quartiles.<sup>11</sup> After the formation month, each portfolio is held for the next twelve-month period either with equal-weighting or value-weighting scheme and we calculate the cumulative portfolio return. This exercise is repeated at the end of each month, and the time-series averages of cumulative portfolio returns are plotted in Figure 1.

Under the equal-weighting scheme, the HBS strategy delivers a series of cumulative returns that is steadily increasing from 1.52% at the first month to 4.09% by the twelfth month of the holding period. Using the same weighting scheme, the cumulative return to the LBS strategy starts at 0.87% at the first month, drops by more than half by the seventh month and reaches 0.17% by the twelfth month of the holding period. The left panel of Figure 1 illustrates the contrast between these two strategies, which is consistent with the two predictions under the investment style hypothesis. Under the value-weighting scheme, a similar pattern holds. The HBS strategy yields 1.23% at the first month and delivers a cumulative return of 1.84% by the twelfth month of the holding period. The LBS strategy yields 0.40% at the first month and -0.23% by the twelfth month of the holding period. A graphic depiction of the contrast between these two strategies in the right panel of Figure 1 makes it clear again that it is rewarding to mimic those insiders who outperform in transaction costs both in the short term and in the long term. Mimicking those insiders with underperformance, on the other hand, pays off only in the short term and suffers attenuating profits and eventual losses in the long term. Therefore, the profitability pattern of mimicking strategies in our sample is consistent with both predictions under the investment style hypothesis. The insider trading data strongly favor the investment style interpretation as in Keim and Madhavan (1997) rather than the trading skill interpretation.

Taken as a whole, the empirical evidence in this paper thus far leads us to three main conclusions. First, insiders are able to beat the market on average and obtain transaction prices that are about 10 cents per share better than volume-weighted average prices even after adjusting for trade difficulty, insider reputation and their role ranks. Second, the level of insider abnormal trading alpha appears to be more of a proxy for the investment style of insiders than a proxy for the trading skill. Insiders with extremely positive abnormal trading alpha resemble value investors who base their decisions on long-term firm fundamentals, trade less aggressively and earn rents from providing liquidity. In contrast, insiders with extremely

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<sup>11</sup>This additional filter is not critical to the success of the said strategies. Repeating the trading strategies after relaxing this filter leads to results that are qualitatively unchanged.

negative abnormal trading alpha resemble those investors who base their decisions on short-lived information, trade more aggressively and pay for demanding immediacy. Finally, those liquidity-providing insiders dominate other insiders who demand immediacy in this sample, and it is profitable for outside investors to mimic the actions of insiders with extremely positive abnormal trading alpha.

#### 4.5 Performance Evaluation of Mimicking Strategies

It appears quite beneficial for outside investors to mimic the trading decisions of insiders after separating insiders on the basis of transaction cost analysis. Suppose that outside investors commit to holding each mimicking portfolio for exactly one month and rebalancing the portfolio every month. The HBS strategy follows insiders who have extremely positive abnormal trading alpha and delivers an annualized portfolio raw return of 18.24% under the equal-weighting scheme (or 14.76% under the value-weighting scheme). The LBS strategy follows insiders with extremely negative abnormal trading alpha and yields an annualized portfolio raw return of 10.44% under the equal-weighting scheme (or 4.80% under the value-weighting scheme). The large magnitude of raw returns prompts us to examine whether the outsize return is due to compensation for exposure to common risk factors. We employ a number of standard factor-pricing models to explain the time series variation of raw portfolio returns to both strategies, including the classic Capital Asset Pricing Model, the Fama-French three-factor model and the Carhart four-factor model. Given the fact that both the HBS and LBS strategies pick stocks on the basis of insider abnormal trading alpha, which is rooted in the transaction costs analysis, it seems prudent to include a factor model that incorporates the aggregate liquidity risk. Out of this consideration, we augment the Carhart four-factor model with the permanent and transitory liquidity factors in Sadka (2006). We also experiment with a version of the Carhart four-factor model augmented with the liquidity factor in Pastor and Stambaugh (2003). Even though there is an ongoing debate on whether or not some of these factors considered above are genuine risk factors, we take no position on this issue and simply view them as standard ways of adjusting for common factors.

Daniel et al. (1997) propose a characteristic-selectivity (CS) measure to control for firm-specific factors such as firm size, book-to-market ratio and trailing-twelve-month return, as an alternative to factor-pricing models for performance evaluation.<sup>12</sup> As in Daniel et al. (1997), we cast all NYSE/AMEX/NASDAQ common stocks (with share code 10 or 11) into 125 bins

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<sup>12</sup>The stock characteristics are constructed as follows. We extract various data items from the annual fundamentals Compustat file and construct the book equity using the definition by Fama and French. Following the Fama and French convention, we allow an accounting disclosure delay of at least six months. That is, the book equity knowable at the end of calendar year  $\tau$  is applied to July of year  $\tau + 1$  through June of year  $\tau + 2$ . Using the market equity in the preceding month, we are able to construct the monthly series of book-to-market ratio. The market equity in the preceding month is also a measure of firm size in the current month. The trailing-twelve-month return for month  $t$  is defined as the cumulative stock return over month  $t - 12$  through  $t - 1$ .

in each month. The classification of the monthly stock bins is the result of creating five groups by each sorting variable, namely the firm size, book-to-market ratio and trailing-twelve-month return, and in that order. The determination of five-group cutoffs relies on NYSE common stocks for the firm size and book-to-market ratio, while the cutoffs for the trailing-twelve-month return utilize all common stocks. For any given month, we compute both the equal-weighted and value-weighted returns separately for the 125 portfolios as benchmark returns. Each stock in the mimicking portfolio corresponds to one respective bin among the 125 benchmark bins, and we calculate the return differential between the stock return and its benchmark portfolio return. The CS measure is the equal- or value-weighted portfolio return differentials.

Table 8 reports the results of performance evaluation using both the factor-pricing models and the CS measure. Regardless of whether we use the equal-weighting or value-weighting scheme, none of the five factor-pricing models is able to make a significant dent on the portfolio return to the HBS strategy. All the estimated intercepts, also known as Jensen’s alpha, are fairly close to the raw portfolio returns in magnitude and remain statistically significant at the 1% level. The CS measure delivers a very similar pattern. Note that in the predictive regression for the one-month-ahead return the dummy variable for the presence of corporate insiders with extremely high trading alpha is positive and statistically significant even after the inclusion of firm size, book-to-market ratio and last-twelve-month return as control variables. Thus it is not surprising that the characteristic-selectivity measure based on the same set of firm-specific factors turns out to be positive and significant. As for the LBS strategy, time-series regressions using five factor-pricing models produce intercepts fairly close to the raw portfolio returns. Moreover, the estimated intercepts are all statistically significant when we use the equal-weighting scheme. The CS measure once again delivers results closely resembling the regression intercepts. Although the estimated intercepts and the CS measure under the value-weighting scheme are mostly indistinguishable from zero from the statistical point of view, this is not surprising given that the value-weighted raw portfolio return to the LBS strategy is fairly close to zero to begin with.

Overall the standard factor-pricing models do not fully explain the profits to the strategies of mimicking insiders with extreme abnormal trading alpha, and this profitability is also robust to adjusting for characteristics selectivity.

## 5 Conclusion

In recent years the corporate insiders in the U.S. have reported transactions at a skyrocketing rate. It becomes increasingly important for market participants, including academics, practitioners and regulators, to glean insights from parsing the insider trades. Examining the insider trading data between 1993 and 2008 in the U.S. from the transaction costs point of

view, we present evidence that corporate insiders as a group obtain transaction prices superior to the volume-weighted average prices for the same stock on the same day, i.e., beating the market. For both insider purchases and sales, there exists a positive and significant abnormal trading alpha of about 10 cents per share on average after adjusting for trade difficulty, insider reputation and the corporate role ranks of insiders.

Outside investors can focus on the insider abnormal trading alpha when designing a long-short strategy to mimic certain groups of insiders. The HBS strategy aims at replicating the trades of outperforming insiders while the LBS strategy targets those underperforming insiders. The time-series patterns of portfolio returns to these strategies yield clues to the source of insider performance in terms of managing transaction costs. We find evidence that the HBS strategy delivers a profit that continues to grow during the 12-month holding period while the profit to the LBS strategy attenuates over time and can turn into a loss by the twelfth month of the holding period. In other words, insiders with extremely negative abnormal trading alpha essentially trade on short-lived information in a rather aggressive fashion as reflected in the eventual attenuation or reversal of profit and the higher transaction costs that they pay. In contrast, insiders with extremely positive abnormal trading alpha seem to resemble value investors that patiently trade on long-term fundamental information and earn rents from providing liquidity. The documented profit pattern for these two mimicking strategies, therefore, is consistent with the notion that the insider abnormal trading alpha reflects the investment style of insiders, echoing the key finding in Keim and Madhavan (1997) for institutional investors.

This paper contributes to the extant literature in several important aspects. First, it documents extensive evidence for the superior trading performance of the corporate insiders in the U.S. at the aggregate level. Second, the trading strategies in this paper are different from conventional strategies based on trading-intensity rules in that our strategies have the micro-foundation of the transaction costs analysis. Therefore, this paper uniquely bridges together the transaction costs literature and the insider trading literature. Moreover, this paper's extension to the investment style hypothesis in Keim and Madhavan (1997) highlights the importance of studying the life cycle of information underlying trades from different corporate insiders and illustrates a new angle through which to analyze insider trades.

While limitations in the insider trading data prevent us from explicitly separating the role of brokers from the role of insiders, it would be interesting to examine whether our results extend to a setting where we can measure the relative contribution of brokers to the management of transaction costs. It will also be interesting to study how the timing of corporate events (such as announcements of earnings and mergers and acquisitions) is related to the profitability of outsider strategies mimicking insider trades. We leave this and other empirical topics for future research.



## References

- [1] Ahmet, Can Inci, Biao Lu, and H. Nejat Seyhun, 2006, Informational role of insider trading, *Florida State University Working Paper*.
- [2] Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2009, Performance of institutional trading desks: An analysis of persistence in trading cost, *Syracuse University Working Paper*.
- [3] Arnott, Robert D., and Wayne H. Wagner, 1990, The measurement and control of trading costs, *Financial Analysts Journal* 46, 73-80.
- [4] Beebower, Gilbert, and William Priest, 1980, The tricks of the trade, *Journal of Portfolio Management* 6, 36-42.
- [5] Berkowitz, Stephen A., Dennis E. Logue, and Eugene A. Noser, Jr., 1988, The total cost of transactions on the NYSE, *Journal of Finance* 43, 97-112.
- [6] Bessembinder, Hendrik, and Herbert M. Kaufman, 1997, A comparison of trade execution costs for nyse and nasdaq-listed stocks, *Journal of Financial and Quantitative Analysis* 32, 287-310.
- [7] Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.
- [8] Chan, Louis K. C., and Josef Lakonishok, 1995, The behavior of stock prices around institutional trades, *Journal of Finance* 50, 1147-1174.
- [9] Chiyachantana, Chiraphol N., Pankaj K. Jain, Christine Jiang, and Robert A. Wood, 2004, International evidence on institutional trading behavior and price impact, *Journal of Finance* 59, 869-898.
- [10] Cohen, Lauren, Christopher Malloy, and Lukasz Pomorski, 2009, Decoding insider information, *Harvard Business School Working Paper*.
- [11] Collins, Bruce M., and Frank J. Fabozzi, 1991, A methodology for measuring transaction costs, *Financial Analysts Journal* 47, 27-44.
- [12] Conrad, Jennifer, Kevin M. Johnson, and Sunil Wahal, 2003, Institutional trading and alternative trading systems, *Journal of Financial Economics* 70, 99-134.
- [13] Conrad, Jennifer S., Kevin M. Johnson, and Sunil Wahal, 2001, Institutional trading and soft dollars, *Journal of Finance* 56, 397-416.
- [14] Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.
- [15] Goldstein, Michael A., Paul Irvine, Eugene Kandel, and Zvi Wiener, 2009, Brokerage commissions and institutional trading patterns, *Review of Financial Studies* 22, 5175-5212.

- [16] Hu, Gang, 2007, VWAP cost excluding own trades, *Journal of Trading* Winter, 30-34.
- [17] Hu, Gang, 2009, Measures of implicit trading costs and buy-sell asymmetry, *Journal of Financial Markets* 12, 418-437.
- [18] Huang, Roger D., and Hans R. Stoll, 1996, Dealer versus auction markets: A paired comparison of execution costs on nasdaq and the nyse, *Journal of Financial Economics* 41, 313-357.
- [19] Jeng, Leslie A., Andrew Metrick, and Richard Zeckhauser, 2003, Estimating the returns to insider trading: A performance-evaluation perspective, *Review of Economics and Statistics* 85, 453-471.
- [20] Jones, Charles M., and Marc L. Lipson, 2001, Sixteenths: Direct evidence on institutional execution costs, *Journal of Financial Economics* 59, 253-278.
- [21] Keim, Donald B., and Ananth Madhavan, 1995, Anatomy of the trading process empirical evidence on the behavior of institutional traders, *Journal of Financial Economics* 37, 371-398.
- [22] Keim, Donald B., and Ananth Madhavan, 1996, The upstairs market for large-block transactions: Analysis and measurement of price effects, *Review of Financial Studies* 9, 1-36.
- [23] Keim, Donald B., and Ananth Madhavan, 1997, Transactions costs and investment style: An inter-exchange analysis of institutional equity trades, *Journal of Financial Economics* 46, 265-292.
- [24] Keim, Donald B., and Ananth Madhavan, 1998, The cost of institutional equity trades, *Financial Analysts Journal* 54, 50-69.
- [25] Lakonishok, Josef, and Inmoo Lee, 2001, Are insider trades informative?, *Review of Financial Studies* 14, 79-111.
- [26] Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.
- [27] Lert, Peter, 2001, Methods of measuring transaction costs, in Brian R. Bruce, ed.: *Transaction costs - a cutting-edge guide to best execution* (Institutional Investor Inc., New York).
- [28] Madhavan, Ananth, and Minder Cheng, 1997, In search of liquidity: Block trades in the upstairs and downstairs markets, *Review of Financial Studies* 10, 175-203.
- [29] Macey, Jonathan R., and Maureen O'Hara, 1997, The law and economics of best execution, *Journal of Financial Intermediation* 6, 188-223.
- [30] Madhavan, Ananth, 2002, VWAP strategies, *Institutional Investor Journals* Spring, 32-38.

- [31] Pástor, Luboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.
- [32] Perold, André F., 1988, The implementation shortfall: Paper versus reality, *Journal of Portfolio Management* 14, 4-9.
- [33] Rozeff, Michael S., and Mir A. Zaman, 1998, Overreaction and insider trading: Evidence from growth and value portfolios, *Journal of Finance* 53, 701-716.
- [34] Sadka, Ronnie, 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309-349.
- [35] Schwartz, Robert A., and J. Shapiro, 1992, The challenge of institutionalization for the equity markets, in Anthony Saunders, ed.: *Recent developments in finance* (New York University Solomon Center, New York).
- [36] Schwartz, Robert A., and Benn Steil, 2002, Controlling institutional trading costs, *Journal of Portfolio Management* 28, 39-49.
- [37] Schwartz, Robert A., and Robert A. Wood, 2003, Best execution, *Journal of Portfolio Management* 29, 37-48.
- [38] Seppi, Duane J., 1990, Equilibrium block trading and asymmetric information, *Journal of Finance* 45, 73-94.
- [39] Seyhun, H. Nejat, 1986, Insiders' profits, costs of trading, and market efficiency, *Journal of Financial Economics* 16, 189-212.
- [40] Seyhun, H. Nejat, 1998. *Investment intelligence: From insider trading* (MIT Press, Cambridge).
- [41] Wagner, Wayne H., and Michael Banks, 1992, Increasing portfolio effectiveness via transaction cost management, *Journal of Portfolio Management* 19, 6-11.
- [42] Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655-1695.
- [43] Wermers, Russ, 2004, Is money really smart? New evidence on the relation between mutual fund flows, manager behavior and performance persistence, *University of Maryland Working Paper*.

**Table 1. Summary Statistics on Corporate Insider Purchases**

This table provides the annual summary statistics of corporate insider purchases of stocks from 1993 to 2008. We apply a number of filters to Thomson Financial Insider Trading database before calculating the summary statistics. These filters include: the reported transaction price falls between \$5 and \$500; the number of shares traded is at least 100 and less than the daily stock share volume reported by the CRSP database; the firm identifiers can be matched with the CRSP database; and transactions are reported on Form 4. For each year between 1993 and 2008, the table reports summary statistics on the number of insiders, number of trades, number of days on which insiders trade, total share volume (in million shares) and total dollar volume (in million dollars).

Year	Insiders	Trades	Days	Share Volume	Dollar Volume
1993	225	497	205	1	24
1994	314	804	223	3	39
1995	857	1,577	234	10	199
1996	5,542	12,721	254	68,142	1,416
1997	5,951	15,203	253	107,342	2,093
1998	7,961	25,406	252	209,070	3,630
1999	8,028	26,938	250	239,590	4,312
2000	6,629	21,793	251	199,097	3,849
2001	4,084	13,672	248	134,288	2,226
2002	4,505	23,050	252	148,182	1,922
2003	3,889	16,996	252	136,423	2,161
2004	4,348	21,896	251	145,025	2,201
2005	4,658	27,388	252	151,356	2,841
2006	4,600	27,435	251	286,181	5,599
2007	6,198	36,717	251	336,475	6,907
2008	6,462	47,179	231	511,148	8,632

**Table 2. Summary Statistics on Corporate Insider Sales**

This table provides the annual summary statistics of corporate insider sales of stocks from 1993 to 2008. We apply a number of filters to Thomson Financial Insider Trading database before calculating the summary statistics. These filters include: the reported transaction price falls between \$5 and \$500; the number of shares traded is at least 100 and less than the daily stock share volume reported by the CRSP database; the firm identifiers can be matched with the CRSP database; and transactions are reported on Form 4. For each year between 1993 and 2008, the table reports summary statistics on the number of insiders, number of trades, number of days on which insiders trade, total share volume (in million shares) and total dollar volume (in million dollars).

Year	Insiders	Trades	Days	Share Volume	Dollar Volume
1993	480	1,125	235	11,143	284
1994	447	1,109	230	11,215	308
1995	1,382	3,219	246	40,017	1,075
1996	10,094	36,100	254	467	15,286
1997	11,989	47,305	253	536	20,452
1998	11,456	47,802	252	714	31,428
1999	10,156	48,434	250	8,220	41,043
2000	12,309	71,777	251	1,252	67,627
2001	12,073	76,603	248	1,153	37,455
2002	10,927	92,604	252	916	27,246
2003	13,556	165,443	252	1,632	45,176
2004	16,223	215,240	251	2,000	59,006
2005	15,630	252,934	252	1,660	58,293
2006	15,984	296,284	251	1,659	56,134
2007	14,967	341,116	251	1,427	49,883
2008	10,048	193,825	232	997	29,897

**Table 3. Summary Statistics on Insider Trading Alpha**

This table presents the summary statistics of trading alpha separately for insider purchases and insider sales of stocks. To compute the trading alpha, we first find the stock-specific daily volume-weighted average price (VWAP) based on consolidated trades in the New York Stock Exchange Trades and Quotes (TAQ) database. For insider buys, the trading alpha is defined as the VWAP in excess of the reported insider transaction prices. For insider sales, the trading alpha is defined as the reported insider transaction prices net of the VWAP. Panel A provides the summary statistics for the full sample while Panels B through E provide the summary statistics for four sub-sample periods.

	Num of Obs	Mean	Median	Std Dev
Panel A. Full sample: 1993-2008				
Insider Purchases	288,682	0.042	0.020	0.230
Insider Sales	1,720,684	0.036	0.020	0.382
Panel B. Sub-sample: 1993-1996				
Insider Purchases	11,063	0.071	0.040	0.249
Insider Sales	34,952	0.045	0.021	0.382
Panel C. Sub-sample: 1997-2000				
Insider Purchases	76,146	0.060	0.031	0.251
Insider Sales	186,695	0.085	0.040	0.494
Panel D. Sub-sample: 2001-2004				
Insider Purchases	70,548	0.026	0.013	0.205
Insider Sales	490,209	0.036	0.022	0.307
Panel E. Sub-sample: 2005-2008				
Insider Purchases	130,925	0.037	0.018	0.227
Insider Sales	1,008,828	0.027	0.015	0.390

**Table 4. Basic Model of Trade Difficulty**

This table presents the Fama-MacBeth results for the model with basic measures of trade difficulty. The regression specification is

$$TrdAlpha = \alpha_0 + \beta_1 \cdot shares + \beta_2 \cdot mktcap + \beta_3 \cdot tprice + \varepsilon.$$

The dependent variable *TrdAlpha* for insider purchases and sales is defined in Section 2 of the main text. Among the explanatory variables, *shares* denotes the insider choice of share volume, *mktcap* stands for the logarithmic market equity of firm with which the insider is affiliated, and *tprice* is the transaction price that the insider obtains. All variables are measured contemporaneously except the market equity in the preceding month. The regressions are estimated and reported separately for different sub-samples, depending on the trade initiation (purchases versus sales) and the sign of the dependent variable. Insiders with a positive trading alpha are labelled as “liquidity suppliers” and those with a negative trading alpha are labelled as “liquidity demanders.” Inside parentheses are *t*-statistics. Statistical significance at the 10%, 5% and 1% level is denoted by \*, \*\* and \*\*\*, respectively.

	purchases	liquidity demanders	liquidity suppliers	all insiders
<i>intercept</i>	-0.0338	(-1.02)	0.3582 (10.58)***	0.2008 (7.17)***
<i>shares</i>	-0.5646	(-0.85)	0.6983 (0.92)	-0.5539 (-0.96)
<i>mktcap</i>	-0.0013	(-0.66)	-0.0136 (-7.05)***	-0.0084 (-5.01)***
<i>tprice</i>	-0.3239	(-8.16)***	0.4624 (14.27)***	0.0928 (2.89)***
<i>Adj. R<sup>2</sup></i>	0.1015		0.0807	0.0205

  

	sales	liquidity demanders	liquidity suppliers	all insiders
<i>intercept</i>	-0.2223	(-6.92)***	0.4412 (10.50)***	0.1072 (3.47)***
<i>shares</i>	-0.1908	(-0.90)	-0.4697 (-2.49)**	-0.5473 (-4.26)***
<i>mktcap</i>	0.0058	(3.22)***	-0.0165 (-7.02)***	-0.0042 (-2.54)**
<i>tprice</i>	-0.3616	(-18.58)***	0.5107 (19.18)***	0.0999 (5.92)***
<i>Adj. R<sup>2</sup></i>	0.1112		0.1371	0.0105

**Table 5. Extended Model of Trade Difficulty**

This table presents the Fama-MacBeth results for the model with extended measures of trade difficulty. The regression specification is

$$TrdAlpha = \alpha_0 + \beta_1 \cdot shares + \beta_2 \cdot mktcap + \beta_3 \cdot tprice + \beta_4 \cdot return + \beta_5 \cdot volatility + \beta_6 \cdot isnyse + \varepsilon.$$

The dependent variable *TrdAlpha* for insider purchases and sales is defined in Section 2 of the main text. Among the explanatory variables, *shares* denotes the insider choice of share volume, *mktcap* stands for the logarithmic market equity of firm with which the insider is affiliated, *tprice* is the transaction price that the insider obtains, *return* is the daily stock return, *volatility* is the absolute value of daily stock return, and *isnyse* is an indicator for stocks listed on the New York Stock Exchange. All variables are measured contemporaneously except the market equity in the preceding month. The regressions are estimated and reported separately for different sub-samples, depending on the trade initiation (purchases versus sales) and the sign of the dependent variable. Insiders with a positive trading alpha are labelled as “liquidity suppliers” and those with a negative trading alpha are labelled as “liquidity demanders.” Inside parentheses are *t*-statistics. Statistical significance at the 10%, 5% and 1% level is denoted by \*, \*\* and \*\*\*, respectively.

	purchases	liquidity demanders	liquidity suppliers	all insiders		
<i>intercept</i>	0.0729	(1.62)	0.1574	(3.11)***	0.0997	(3.03)***
<i>shares</i>	3.6687	(1.37)	0.8131	(0.76)	-0.9114	(-1.41)
<i>mktcap</i>	-0.0049	(-1.83)*	-0.0049	(-1.57)	-0.0031	(-1.51)
<i>tprice</i>	-0.3414	(-6.40)***	0.4614	(8.55)***	0.0729	(1.89)*
<i>return</i>	0.3261	(1.90)*	0.0360	(0.40)	0.2576	(2.88)***
<i>retvol</i>	-2.0233	(-10.46)***	2.0564	(12.69)***	0.4522	(3.99)***
<i>isnyse</i>	0.0153	(2.85)***	-0.0376	(-6.33)***	-0.0139	(-2.73)***
<i>Adj. R<sup>2</sup></i>	0.2439		0.1974		0.0509	

  

	sales	liquidity demanders	liquidity suppliers	all insiders		
<i>intercept</i>	0.1058	(4.06)***	0.1009	(2.29)**	0.1023	(3.30)***
<i>shares</i>	0.0267	(0.14)	-0.4628	(-3.67)***	-0.4354	(-3.98)***
<i>mktcap</i>	-0.0070	(-4.62)***	-0.0033	(-1.37)	-0.0051	(-3.07)***
<i>tprice</i>	-0.3829	(-19.28)***	0.5170	(23.53)***	0.1163	(7.68)***
<i>return</i>	-0.7484	(-1.83)*	-0.9745	(-12.70)***	-1.1239	(-13.21)***
<i>retvol</i>	-3.3618	(-8.21)***	3.4317	(27.15)***	0.6941	(5.98)***
<i>isnyse</i>	0.0288	(7.65)***	-0.0325	(-6.00)***	0.0029	(0.65)
<i>Adj. R<sup>2</sup></i>	0.2324		0.2452		0.0353	



**Table 6. Role of Insider Characteristics**

This table presents the Fama-MacBeth results for a model that links the insider role and reputation to the abnormal trading alpha adjusted for trade difficulty, *AdjAlpha*. The regression specification is

$$AdjAlpha = \alpha_0 + \gamma_1 \cdot isexecutive + \gamma_2 \cdot isofficer + \gamma_3 \cdot isfinexecutive + \gamma_4 \cdot reputation + \nu.$$

The dependent variable *AdjAlpha* is the sum of the estimated intercept and the regression residual from the model with extended measures of trade difficulty. The explanatory variables include dummy variables based on the role rank of corporate insiders: *isexecutive* is an indicator for top executives, *isofficer* is an indicator for officers or directors, *isfinexecutive* is an indicator for top executives in the financial industry, and we also use one of two measures of *reputation* for insiders. Denote as *reputelast* the volume-weighted abnormal trading alpha for a given insider in the most recent trading day, and denote as *reputecum* the cumulative average abnormal trading alpha as of the trade day. The regression results are reported separately for insider purchases and insider sales. Inside parentheses are *t*-statistics. Statistical significance at the 10%, 5% and 1% level is denoted by \*, \*\* and \*\*\*, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>purchases</i>						
<i>intercept</i>	0.1108 (3.39)***	0.1098 (3.36)***	0.0953 (2.91)***	0.0884 (2.63)***	0.1048 (3.25)***	0.0995 (3.00)***
<i>isexecutive</i>	-0.0145 (-4.31)***	-0.0135 (-3.27)***			-0.0132 (-2.67)***	-0.0121 (-2.62)***
<i>isofficer</i>	-0.0014 (-0.55)	-0.0014 (-0.55)			-0.0038 (-0.85)	-0.0071 (-1.44)
<i>isfinexecutive</i>		0.0079 (1.40)			0.0090 (2.08)**	0.0082 (1.89)*
<i>reputelast</i>			0.0336 (6.57)***		0.0312 (5.86)***	
<i>reputecum</i>				0.0474 (6.46)***		0.0463 (5.92)***
<i>Adj. R</i> <sup>2</sup>	0.0021	0.0038	0.0026	0.0025	0.0249	0.0225
<i>sales</i>						
<i>intercept</i>	0.1088 (3.62)***	0.1087 (3.57)***	0.0992 (3.18)***	0.0947 (3.01)***	0.1076 (3.57)***	0.1017 (3.38)***
<i>isexecutive</i>	-0.0107 (-2.99)***	-0.0106 (-2.90)***			-0.0082 (-1.79)*	-0.0073 (-1.60)
<i>isofficer</i>	0.0024 (0.72)	0.0024 (0.72)			0.0014 (0.31)	0.0023 (0.50)
<i>isfinexecutive</i>		0.0147 (1.85)*			0.0178 (2.23)**	0.0154 (1.80)*
<i>reputelast</i>			0.0333 (6.63)***		0.0319 (6.83)***	
<i>reputecum</i>				0.0598 (7.11)***		0.0591 (7.57)***
<i>Adj. R</i> <sup>2</sup>	0.0010	0.0015	0.0047	0.0040	0.0067	0.0050

**Table 7. Predicting One-Month-Ahead Stock Returns**

This table presents the Fama-MacBeth results for predicting one-month-ahead stock returns. The regression specification is

$$return_{t+1} = \phi_0 + \phi_1 \cdot ishighbuy_t + \phi_2 \cdot islowbuy_t + \phi_3 \cdot ishighsell_t + \phi_4 \cdot islowsell_t + \phi_5 \cdot mktcap_t + \phi_6 \cdot bmratio_t + \phi_7 \cdot ltmret_t + \eta.$$

The dependent variable is the stock return in month  $t + 1$ . Among the explanatory variables measured in month  $t$ , the dummy variable *ishighbuy* (or *ishighsell*) indicates the presence of any insider whose buy (or sell) order is associated with a positive abnormal trading alpha in the top quartile, the dummy variable *islowbuy* (or *islowsell*) indicates the presence of any insider whose buy (or sell) order is associated with a negative abnormal trading alpha in the bottom quartile, *mktcap* is the logarithmic market equity of firms with which insiders are affiliated, *bmratio* is the book-to-market ratio and *ltmret* is the last-twelve-month cumulative return between month  $t - 12$  and  $t - 1$ . Inside parentheses are  $t$ -statistics. Statistical significance at the 10%, 5% and 1% level is denoted by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Intercept</i>	0.0073 (1.99)**	0.0105 (3.03)***	0.0087 (2.52)**	0.0463 (3.76)***	0.0404 (2.52)**	0.0348 (2.25)**
<i>ishighbuy</i>	0.0115 (4.67)***		0.0108 (4.65)***	0.0104 (4.52)***	0.0115 (4.62)***	0.0116 (4.51)***
<i>islowbuy</i>	0.0057 (2.97)***		0.0045 (2.48)**	0.0049 (2.64)***	0.0044 (2.23)**	0.0044 (2.29)**
<i>ishighsell</i>		-0.0047 (-1.96)**	-0.0035 (-1.50)	-0.0021 (-0.85)	-0.0041 (-1.75)*	-0.0058 (-2.67)***
<i>islowsell</i>		-0.0022 (-1.10)	-0.0011 (-0.56)	-0.0006 (-0.28)	0.0008 (0.44)	0.0006 (0.39)
<i>mktcap</i>				-0.0019 (-3.40)***	-0.0017 (-2.40)**	-0.0015 (-2.25)**
<i>bmratio</i>					0.0024 (0.90)	0.0046 (1.92)*
<i>ltmret</i>						0.0055 (2.21)**
<i>Adj. R<sup>2</sup></i>	0.0039	0.0050	0.0081	0.0128	0.0153	0.0317

**Table 8. Performance Evaluation of Mimicking Strategies**

This table presents selected results from using various factor-pricing models to explain the portfolio returns to strategies based on abnormal trading alpha. The HBS strategy mimics the actions of insiders who have positive abnormal trading alpha within the top quartile, and the LBS strategy mimics the actions of insiders who have negative abnormal trading alpha within the bottom quartile. The portfolio is formed at the end of each month, held for one month, and rebalanced at the end of each month. The monthly portfolio returns under the equal-weighting (or value-weighting) scheme are denoted by *ewretHBS* and *ewretLBS* (or *vretHBS* and *vretLBS*). We report the estimated intercepts from the time series regressions of portfolio returns using a number of standard factor-pricing models, which include the CAPM model, the Fama-French three-factor model, the Carhart four-factor model, the Carhart four-factor model augmented by two liquidity factors in Sadka (2006), and the Carhart four-factor model augmented by the liquidity factor in Pastor-Stambaugh (2003). We also report the time series average portfolio returns adjusted for firm-specific factors such as size, book-to-market ratio and last-twelve-month return using the characteristic-selectivity (CS) measure in Daniel et al. (1997). Inside parentheses are *t*-statistics. Statistical significance at the 10%, 5% and 1% level is denoted by \*, \*\* and \*\*\*, respectively.

	<i>ewretHBS</i>	<i>ewretLBS</i>	<i>vretHBS</i>	<i>vretLBS</i>
CAPM Alpha	0.0140 (3.72)***	0.0089 (2.84)***	0.0110 (2.83)***	0.0044 (1.10)
Fama-French 3-Factor Alpha	0.0134 (3.50)***	0.0077 (2.43)**	0.0111 (2.81)***	0.0038 (0.93)
Carhart 4-Factor Alpha	0.0126 (3.23)***	0.0071 (2.21)**	0.0113 (2.79)***	0.0050 (1.20)
Pastor-Stambaugh 5-Factor Alpha	0.0128 (3.23)***	0.0072 (2.21)**	0.0115 (2.79)***	0.0043 (1.02)
Sadka 6-Factor Alpha	0.0158 (3.31)***	0.0083 (2.14)**	0.0149 (3.09)***	0.0090 (1.99)**
Daniel et al. CS Measure	0.0171 (6.13)***	0.0101 (4.22)***	0.0112 (3.99)***	0.0046 (1.50)

**Figure 1. Cumulative Portfolio Returns to Mimicking Strategies**

This figure plots the cumulative portfolio returns to two strategies of picking stocks based on the insider abnormal trading alpha. The HBS strategy mimics the actions of insiders who have positive abnormal trading alpha within the top quartile, while the LBS strategy mimics the actions of insiders who have negative abnormal trading alpha within the bottom quartile. The investment on the buy side is worth \$1, as is the investment on the sell side. After the formation month, each portfolio is held for the next twelve-month period with equal-weighting (or value-weighting) scheme and we calculate the cumulative portfolio return for each strategy. This exercise is repeated at the end of each month, and we plot below the time-series averages of cumulative portfolio returns.

