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ABSTRACT

We show that the stock selection ability of a fund manager can be decomposed into two components: "informed trading" and "liquidity provision." As information loses value over time, informed trading tends to be liquidity-absorbing. We conjecture that value enhancing informed trading is more likely in stocks during times when they are associated with more information events. In contrast, liquidity provision is more likely to add value for stocks associated with few information events and little adverse selection risk. We identify times when there are more information events associated with a stock by its Probability of Informed Trading (PIN, Easley et. al., 1996) measure and information asymmetry component of the spread (Madhavan et. al., 1997). We provide empirical support for our conjecture using quarterly mutual fund holdings data for the period from 1983 to 2004. We find that the informed trading component is relatively more important for mutual funds with a growth oriented investment style whereas liquidity provision is more important for funds with more of an income orientation. Further, the informed trading component of the selection ability of a mutual fund exhibits greater persistence over time.

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As of 2006, US mutual fund managers collectively have over $10 trillion under their management with almost $6 trillion of it equity funds. A significant portion of this amount is actively managed. For example, in 2006 alone, US mutual funds bought and sold common stocks worth over $6 trillion.[1] Naturally, investors would like to understand how active fund managers add sufficient value to justify their higher fees relative to passively managed index funds.

The early literature on portfolio performance evaluation find that most managed portfolios earn close to zero or negative risk-adjusted returns especially after taking fees into account.[2] In contrast, more recent studies that make use of quarterly reports of mutual funds stock holdings find active managers possess considerable stock-picking abilities.[3] On average, after adjusting for the stock characteristics but before deducting fees and expenses, stocks held by mutual funds outperform their benchmarks and stocks bought by mutual funds tend to outperform those sold by mutual funds. Further several mutual fund characteristics appear to be related to superior stock-selection skills. For example, funds that follow "aggressive growth" and "growth" styles (Daniel, Grinblatt, Titman and Wermers, 1997); hold stocks of firms whose headquarters are located geographically closer to the fund's headquareters (Coval and Moskowitz, 2001); have more industry concentration in their holdings (Kacperczyk, Sialm and Zheng, 2004; Lubomira, 2005); have less diversification in their holdings (Baks, Busse and Green, 2006); have larger deviations from passive index or larger "active shares" (Cremers and Petajisto, 2006); and less dependency on analyst's recommendation (Kacperczyk and Seru, 2007) tend to perform better. In addition funds that are smaller in size (Chen, Hong, Huang and Kubik, 2004) perform better. We add to this latter literature by showing that the stock selection ability of an active portfolio manager can be decomposed into the following two components based on knowledge of what stocks the manager holds: liquidity absorbing informed trading and liquidity provision. Such a decomposition will facilitate individual and institutional investors understand the strengths of an active portfolio manager and the extent to which such strengths will continue to be of value in the future.

Ultimately, an active mutual fund manager's skill comes from superior ability to process valuation-relevant information on a stock that helps correctly identify potential mispricing. How a manager

[1] These numbers are taken from Table 3 and 30 of the Mutual Fund Facts Book (2007) published by the Mutual Fund Institute.

[2] See Jensen (1968), Gruber (1996) and Carhart (1997)

[3] See Grinblatt and Titman (1989, 1993), Wermers (1997), Daniel, Grinblatt, Titman and Wermers (1997), Chen, Jegadeesh and Wermers (2000), Schultz (2007)

with superior skill trades to add value will depend on how long it takes for the market to realize that the manager is right. Based on the how long the informational advantage lasts, a manager's trades can be classified into the following three types. (i) The manager can add value from long-term "value investing" by taking a position in a stock expecting the market to eventually agree with her view in, say, a few years.[4] In that case, the exact timing of trades would not be critical. Evaluating the stock selection skill of such a portfolio manager who makes a few concentrated long term bets will be difficult based only on quarterly observations on what the manager holds. (ii) The manager can add value from medium-term informed trading by transacting in "mispriced" stocks expecting the market to agree with her view within, say, a quarter or two.[5] In that case the value of the information is likely to erode quickly over time and trades may have to be executed by paying a substantial price concession for immediacy. (iii) The manager can add value from short-term liquidity provision by taking the other side of a trade when liquidity is most needed.[6] Since fund managers often hold an inventory of stocks in order to track their performance benchmarks, they have a natural advantage in making a market in those stocks. The superior knowledge about the stocks covered by a manager will help in any market making activities by minimizing potential losses that may arise by trading with those with an information advantage. In this paper our focus is on identifying how much of the value added by a manager comes from (ii) and (iii) above.

While in theory knowledge of what the manager holds should help evaluate a portfolio manager's skill better, the fact that mutual fund stock holdings data are available only at infrequent intervals

[4]Using fundamental analysis, Mario Gabelli, a money manager, realized that the stock of Hudson General Corp (HGC) was heavily undervalued at around \$25 in early 1994 and started to accumulate shares of HGC for his Gabelli funds (see Figure 1A). The investment started to payoff after two years when the stock price increased to \$40. The market eventually agreed with Mr. Gabelli when Lufthansa took over HGC at \$76 per share. See Greenwald, Kahn, Sonkin and Biema (2001) for details on this case.

[5]The year-to-year same store sales growth reported by Starbucks every month is a widely watched number and is considered about as important as its quarterly earnings announcements for valuation purposes. During January to September 2005, Starbucks' reported sales growth rates were in the range of 7% to 9%. Most analysts were of the view that a large part of that growth rate was attributable to the 3% sales price increase took place in October 2004, and will not help in same month year to year sales growth starting Oct 2005. That probably explains the much smaller expected growth rate (analyst's consensus was 3.6%). However, a careful analysis of sales breakdown would have indicated that the 3% price increase in October 2004 contributed little to explain the sales growth during January-September 2005. So, the October sales growth figure should be more like that for the earlier months in 2005. While most mutual funds decreased their holdings of Starbucks stock during Q3 of 2005, in anticipation of a drop of same-store sales growth announcement for Oct, Putnam Voyager Fund actually accumulated more shares (see Figure 1B). On November 3, 2005 Starbucks reported a more-than-solid sales growth of 7% for Oct and its share price jumped. Details on this case can be found in Blumenthal (2007).

[6]It is well known that when index funds trade following index rebalancing, their trades tend to demand liquidity from the market (see Blume and Edelen, 2004). Active fund managers taking the other side of those trades will benefit from liquidity provision.

(quarterly in most cases) makes it difficult to assess a manager's abilities when the manager trades actively in between two holdings reporting points in time.[7] This is especially true for studying a managers' short-term liquidity provision since we are only able to, at best, capture the partial effect of a liquidity shock that persist over a calendar quarter end. In spite of this limitation, a mutual fund's recent trades inferred from their quarterly holding changes, still contain interesting information about a manager's abilities, especially in medium-term informed trading, if we can separate the medium-term informed trading from short-term liquidity provision in order to reduce the noise in the data. That becomes possible when we recognize that informed trading tends to be liquidity-absorbing on average since information loses value over time. In addition, we can further improve the identification of managers' skills by conditioning on the amount of private information associated with the stocks they trade. In particular, we conjecture: (1) as informed trading adds value from superior information-processing skills, value enhancing informed trading is more likely to take place in stocks during times when they are associated with more information events; (2) liquidity provision is more likely to add value for stocks associated with few information events and therefore little adverse selection risk (Glosten and Harris, 1998). To measure the frequency and intensity of private information events, we consider two market microstructure based measures: (a) The Probability of Informed Trading (PIN) measure proposed by Easley, Kiefer, O'Hara and Paperman (1996), and (b) The information asymmetry component of the bid-ask spread proposed by Madhavan, Richardson and Roomans (1997).

We therefore decompose the stock selection skill of a manager into a liquidity absorbing informed trading component, a liquidity providing component, and other components using quarterly mutual fund holdings data from 1983 to 2004. We start with the holdings based measure of stock selection skill, "Characteristic Selectivity (CS)," that was proposed by Daniel, Grinblatt, Titman and Wermers (DGTW, 1997). CS measures the extent to which managers can select stocks that outperform the average stocks having the same characteristics.[8] We first decompose the CS measure into three components: a passive "buy-and-hold" component (CS^P), a small adjustment compo-

[7] For instance, Kacperczyk, Sialm and Zheng (2007) and Elton et. al. (2006) show that the "unobservable" actions (or high-frequency turnovers) by mutual funds could be important for some funds. Campbell, Ramadorai and Schwartz (2007) attempts to infer insitutional transactions within a quarter by selecting trade sizes to best match quarterly holding changes. Relying a unique regulation of mutual fund trades disclosure in Canada, Christoffersen, Keim and Musto (2006) investigate essentially all trades of 210 Canadian mutual funds between 2001 and 2003.

[8] Chan, Dimmock and Lakonishok (2006) discuss a variaty of performance benchmarks and conclude that characteristic matching method may generate better tracking ability than regression-based procedures.

nent due to fund flows (CS^{adj}) and an active component due to trading in the previous quarter (CS^A). The active component (CS^A) which captures return to managers' recent trades are more informative about their stock selection skills. CS^A can be further decomposed into an informed trading component (CS^{inf}) and a liquidity provision component (CS^{liq}), respectively. The last decomposition is motivated by the evidence that the stock level aggregate order imbalance serves as a good measure of the direction of liquidity needs on the underlying stock (see Chordia and Subrahmanyam, 2004 among others). When managers trade in the same direction as the aggregate market order imbalance, they demand liquidity. Such trades are therefore likely driven by information and are classified as "informed trading." On the other hand, when managers trade in the opposite direction of the aggregate market order imbalance, they supply liquidity effectively and such trades are classified as "liquidity provision" although sometimes they may not be directly motivated by the "liquidity provision" objective.[9]

We show that when fund managers open new positions and close out or increase existing positions, they are likely to absorb market liquidity. When they decrease existing positions, they are likely to provide liquidity, consistent with our earlier conjecture that it is easier to provide liquidity on stocks currently in one's possession. We also demonstrate the effectiveness of this decomposition approach in two specific cases: (1) Dimensional Fund Advisors (DFA) and (2) a group of index funds.[10] We confirm that the decomposition results in those two cases are largely consistent with what one would expect. We then apply the decomposition to portfolios of active mutual funds sorted by the trade-value-weighted-average-PIN of stocks they recently traded ($trade\_PIN$).[11]

Several interesting patterns emerge. First, funds trading high-PIN stocks outperform those trading low-PIN stocks by 52.9 bps per quarter (t-value = 2.87) after controlling for stock char-

[9]For example, consider a mutual fund that has a policy of not investing more than a certain percentage of its assets in any one stock. That a fund may decrease it holdings of a stock that experienced a recent sharp price increase in order to satisfy its portfolio weight constraints. Such trades are likely to provide liquidity and will therefore be classified as "liquidity provision" even when liquidity provision was not the motive behind the trade.

[10]Keim (1999) finding that the small-cap equities "9-10 fund" of Dimensional Fund Advisors (DFA) outperformed its benchmark by about 2.2% during the period between 1982 to 1995, illustrates how skillful trade execution can enhance fund performance. Cohen (2002) documents that managers at DFA add value by systematically providing liquidity to those who want to trade small cap stocks for non-information based reasons. We verify that most of the value added by DFA through stock selection indeed comes from the liquidity provision component (CS^{liq}).

[11]Easley, Hvidkjaer and O'Hara (2002) document that High-PIN stocks earn higher returns on average. They interpret this as being compensation for risk associated with private information, i.e., PIN-risk. That should not drive our results – both stocks that mutual funds buy and sell funds have about the same PIN values, but stocks bought by mutual funds tend to outperform those sold by mutual funds. Further, we show that our findings are not driven by momentum trading rules described in the literature. Finally, our results are not sensitive to the choice of PIN as the measure of the amount of information events affecting a stock.

acteristics such as size, book-to-market ratio and return momentum. Using after-fee mutual fund returns from CRSP mutual fund database, we obtain similar results. Specifically, funds trading high-PIN stocks outperform those trading low-PIN stocks by 50.5 bps per quarter (t-value = 3.27) after four-factor risk adjustment (Fama and French, 1993 and Carhart, 1997), indicating that the better performance is unlikely to be driven by the window dressing actions of mutual funds.

Second, a large part of the CS measure for high-$trade\_PIN$-funds (total stock selectivity, CS = 50 bps) indeed comes from active trading during the previous quarter ($CS^A = 31.2$ bps). Although both the informed trading component (CS^{inf}) and the liquidity provision component (CS^{liq}) are positive for high-$trade\_PIN$-funds, only the the informed trading component is significant (20.4 bps with t-value of 2.25) and its size is twice that of the liquidity provision component (10.4 bps). The liquidity provision component is positive – certain skilled managers, by judiciously choosing their trades, could potentially benefit from the price impact working to their advantage, which could be sizable for high-PIN stocks. However, for all funds trading high-PIN stocks as a group, the positive liquidity provision is not significant (t-value = 1.37), probably because for most managers in this group this is a smaller fraction of the trades they execute. Moreover, some difficulty comes with detecting high-frequency liquidity events using quarterly holdings data.

Third, we document a positive significant liquidity provision component ($CS^{liq} = 16.2$ bps per quarter with t-value of 2.57) for funds trading low-PIN stocks. For low-PIN stocks, fund managers are less likely to encounter informed traders when they trade. Consequently, when they trade against the market order imbalance, they are more likely to benefit from the price impact.

We obtain qualitatively very similiar results when we use (1) an alternative PIN measure (rel_oimb, Aktas, Bodt, Declerck and Oppens, 2007 and Kaul, Lei and Stoffman, 2007) and (2) the information asymmetry component of the bid-ask spread as an alternative measure of private information (Madhavan, Richardson and Roomans, 1997). Using a cross-sectional regression framework, we identify fund characteristics that are associated with informed trading and liquidity provision. We first confirm that funds trading high-PIN stocks have a larger informed trading component. Second we find that funds with a growth oriented investment style are more likley to engage in informed trading and younger funds and funds with income-oriented investment style more likely to engage in liquidity provision. Finally, we document that the informed trading component of the skill of a mutual fund appears to persist for a while from one quarter into the next.

The standard pratice in portfolio performance appraisal is to decompose the skill (value added) by a manager into two major components: Security Selection and Market Timing. The reason behind such a decomposition is the assumption that the two types of skills are different, and the value added by these two components require the use of different asset pricing models (linear factor models for valuing selection and contingent claims framework for valuing asset allocaiton). We suggest a further decomposition of the former component depending on whether the the manager's stock trade absorbs or provides liquidity. The motivation for such a decomposition is based on our reading of the empirical market microstructure literature: providing liquidity requires specialization and may well require a different type of talent. Consequently, our decomposition would further improve the evaluation of mutual fund managers' skill and help to better predict funds' performance in the future.

The remainder of this paper is organized as follows. We describe our data sources and the sample in section 1, and illustrate our approach to decomposing the stock selection ability of a mutual fund manager into its informed trading, liquidity provision, and residual components in section 2. We then present our main empirical findings in section 3 and conclude in section 4. The appendices contain a numerical example on skill decomposition, a brief discussion on the variance decomposition approach, and brief descriptions of various measures of private information events.

1 Data and Sample Construction

We employ data from several sources. The mutual fund holding data come from the CDA/Spectrum $S12$ mutual fund holding database, which collects the holding information from the N30-D filings to the Security and Exchange Commission (SEC). A detailed description of the database can be found in Wermers (1999). We exclude index funds and lifecylce funds as these are hybrid funds.[12] In addition, following the standard practice in the mutual fund literature, we omit international funds, sector funds, bond funds, and domestic hybrid funds based on the self-reported fund style in the CDA/Spectrum database. Thus, we only keep funds that are self-reported as Aggressive Growth (AGG), Growth or Growth and Income (GNI). To ensure that the funds we examine are

[12] Specifically, we exclude a fund if its name contains any of the following: "INDEX", "INDE", "INDX", "S&P", "DOW JONES", "MSCI" or "ISHARE".

reasonably active, we only include fund / quarter observations if the fund trades at least 10 stocks and turns over at least 10% of its holdings during that quarter. Finally, we only include fund / quarter observations for which the fund holdings at the end of previous quarter are also available so holding changes can be computed over consecutive quarters. We obtain the information on the after-fee performance of the fund and other fund characteristics from the CRSP survivor-bias-free mutual fund database.

The CDA/Spectrum mutual fund holding data are matched to CRSP Mutual Fund data using the MFLINKS database produced by the Wharton Research Data Service (WRDS) and updated by Professor Russ Wermers. An appealing feature of MFLINKS database is that it allows us to map different share classes of the same fund, that are recorded as distinct funds in the CRSP Mutual Fund database, to the corresponding mutual fund holdings data in the CDA/Spectrum database. For multiple share classes in CRSP that correspond to the same fund in the CDA/Spectrum database, we aggregate those share classes into one large portfolio by equal-weighting or value-weighting (using the total net asset values). The results for equal-weighting and value-weighting are similar, although we report the results only for the former case.

The stock data come from the Center for Research in Security Prices (CRSP). We include all common stocks (CRSP share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ. The accounting information comes from COMPUSTAT database. To link COMPUSTAT and CRSP, we use CRSP-LINK produced by CRSP. The tick-by-tick stock transaction data come from ISSM (1983 to 1992) and TAQ (1993 to 2004) databases.

Overall, there are $4,654$ distinct funds in our sample during the period from 1983 to 2004. On average, there are about 701 distinct funds every quarter. The number of funds per quarter increases from about 134 in 1983 to about $1,700$ towards the end of the sample as shown in Table 1. About 61% of the funds in our sample are self-reported as "Growth" funds, about 26% are reported as "Growth and Income (GNI)" and the remaining 13% are reported as "Aggressive Growth (AGG)".

We collect two groups of fund-level characteristics every quarter. First, we obtain common fund characteristics from CRSP mutual fund database. These characteristics include: *age* (the age of the fund in months since inception, in terms of percentile rank in the cross-section);[13] *turnover* (the turnover rate of the fund); *expense* (the expense ratio of the fund); TNA (the total net assets

[13] We use percentile age ranks to remove a time-series (increasing) trend in the age variable.

under management by the fund in millions US$); and pct_flow (the net fund flows in percentage defined as $\frac{TNA(t)-TNA(t-1)*(1+Ret(t-1,t))}{TNA(t-1)}$). Second, we aggregate stock characteristics at fund level by value-weighing them for stocks held by the fund using the quarter-end dollar values of the holdings. These characteristics include: $fund\_holding$ (average percentage of total number of shares outstanding of stocks held by the fund); $fund\_size$ (average market capitalization of stocks held by the fund, in billion dollars); $fund\_bm$ (average book-to-market ratio of stocks held by the fund), $fund\_mom$ (average past one-year return on stocks held by the fund) and $fund\_amihud$ (average Amihud illiquidity measure, in terms of percentile rank in the cross-section, of stocks held by the fund).[14]

2 A Decomposition of a Fund's Stock Selection Skill

Daniel, Grinblatt, Titman and Wermers (DGTW, 1997) and Wermers (2004) develop a "Characteristic Selectivity" (CS) measure to detect whether managers can select stocks that outperform the average stocks with the same characteristics. By examining the actual stock holdings of the mutual fund, its CS measure during quarter $t+1$ is computed as,

$$CS_{t+1} = \sum_{j} w_{j,t} \left[R_{j,t+1} - BR_{t+1}\left(j,t\right) \right], \tag{1}$$

where $R_{j,t+1}$ is the return on stock j during quarter $t+1$, $BR_{t+1}(j,t)$ is the benchmark portfolio return during quarter $t+1$ to which the stock j is matched at the end of quarter t based on its size, book-to-market equity ratio, and past 12-month return; and $w_{j,t}$ is the dollar value weight of stock j held by the mutual fund at the end of quarter t. In this section, we propose a further decomposition of the CS measure. A numerical example is provided in Appendix A.

Suppose mutual funds rebalance only at discrete points in time, t = 1, 2, 3, ...T. For convenience we assume that time periods are measured in quareters.[15] Let N_t be a column vector

[14] Amihud illiquidity measure is defined as the average ratio between absolute daily return and daily dollar volume. We use percentile Amihud ranking for two reasons. First, there is a time-series (downward) trend in the Amihud measure due to an increase in trading volume; second, the Amihud measure may be extreme and subject to outliers. Using percentile ranking alleviates these issues.

[15] In practice, mutual funds will trade in between quarters as well. That introduces a specification error in our empirical analysis. However, our diagnostics suggest our findings are unlikely to be biased due to that specification error.

of mutual fund stock holdings (in number of shares, split adjusted) at the end of quarter t. By comparing N_{t-1} and N_t, three stock portfolios can be defined:

(1) "Hold" portfolio, whose stock holdings are:

$$N_t^H = \min\left(N_{t-1}, N_t\right),$$

where the operator min() calculates the element-by-element minimum. N_t^H captures holdings that appear in both quarters.

(2) "Buy" portfolio, whose stock holdings are:

$$N_t^B = N_t - N_t^H.$$

"Buy" portfolio contains stocks bought by the fund during quarter t.

(3) "Sell" portfolio, whose stock holdings are:

$$N_t^S = N_{t-1} - N_t^H.$$

"Sell" portfolio contains stocks sold by the fund during quarter t.

Over time, the mutual fund stock holdings change as follows:

$$N_t = N_{t-1} - N_t^S + N_t^B.$$

Let P_t be a column vector of corresponding stock prices at the end of quarter t and denote the market value of "Hold", "Buy" and "Sell" portfolios as H_t, B_t and S_t accordingly, we have:

$$\begin{aligned} H_t &= P_t' N_t^H, \\ B_t &= P_t' N_t^B, \\ S_t &= P_t' N_t^S. \end{aligned}$$

At the end of quarter t, the mutual fund stock holding is a combination of the "Hold" portfolio and "Buy" portfolio. The fund CS measure for quarter $t+1$ is therefore the value-weighted average of CS measures on the "Hold" portfolio and "Buy" portfolio for quarter $t+1$:

$$CS_{t+1} = \frac{H_t}{H_t + B_t} CS_{H,t+1} + \frac{B_t}{H_t + B_t} CS_{B,t+1},$$

where $CS_{H,t+1}$ and $CS_{B,t+1}$ denote CS measure on "Hold" and "Buy" portfolios for quarter $t+1$, respectively.

We then decompose the CS measure into three components:

$$\begin{aligned} CS_{t+1} &= CS^P_{t+1} + CS^A_{t+1} + CS^{adj}_{t+1}, \\ CS^P_{t+1} &= \frac{H_t}{H_t + S_t} CS_{H,t+1} + \frac{S_t}{H_t + S_t} CS_{S,t+1}, \\ CS^A_{t+1} &= \frac{B_t}{H_t + B_t} CS_{B,t+1} - \frac{S_t}{H_t + S_t} CS_{S,t+1}, \\ CS^{adj}_{t+1} &= \frac{H_t}{H_t + B_t} \frac{S_t - B_t}{H_t + S_t} CS_{H,t+1}. \end{aligned} \tag{2}$$

The first component, CS^P_{t+1}, can be interpreted as the CS measure on the fund as if the fund adopts a passive strategy by holding on to the shares for one more quarter.[16] If nothing happens to the fund during quarter t, its stock holding would remain unchanged ($N_t = N_{t-1}$) and would be comprised of stocks in the "Hold" portfolio and "Sell" portfolio. Consequently, the CS measure for quarter $t+1$ would be the value-weighted average of CS measures on the "Hold" portfolio and "Sell" portfolios. The second component, CS^A_{t+1}, which measures the characteristics-adjusted returns to the recent mutual fund stock trades, captures the value-added from active fund trading during quarter t. As most fund managers are evaluated by comparing their performance against a performance benchmark, a large part of their holdings are chosen to minimize benchmark tracking errors. As a result, the active component (CS^A) is often more informative with regard to their stock selection skills. Finally, CS^{adj}_{t+1} represents an adjustment term whenever $S_t \neq B_t$, which could happen when there is inflow or outflow to the fund for example.

We then further decompose the active trading component CS^A_{t+1} into two components by comparing the sign of quarterly mutual fund holding change and the sign of market order imbalance for each stock traded by the fund (the stocks in the "Buy" or "Sell" portfolio) during quarter t.

[16]Note that we use the term "passive" for convenience. What appears "passive" from our perspective could be due to positions the fund manager took based on longer term views.

The market order imbalance is defined as the total number of buyer-initiated trades minus the total number of seller-initiated trades in the quarter. Consistent with the literature, the trade classification is done using the standard algorithm in Lee and Ready (1991). We then classify stock trades where the two signs are identical into one group denoted using superscript "+" and those where the two signs are different into another group denoted using superscript "−". As a result, the characteristics-adjusted returns on trades from these groups sum up to CS^A_{t+1}:

$$\begin{aligned} CS^A_{t+1} &= CS^{inf}_{t+1} + CS^{liq}_{t+1}, \\ CS^{inf}_{t+1} &= \frac{B^+_t}{H_t + B_t} CS^+_{B,t+1} - \frac{S^+_t}{H_t + S_t} CS^+_{S,t+1}, \\ CS^{liq}_{t+1} &= \frac{B^-_t}{H_t + B_t} CS^-_{B,t+1} - \frac{S^-_t}{H_t + S_t} CS^-_{S,t+1}. \end{aligned} \tag{3}$$

Given that the aggregate market order imbalance is a good measure of the direction of liquidity needs on the stock (see Chordia and Subrahmanyam, 2004), CS^{inf}_{t+1} measures the characteristics-adjusted return on mutual fund trades that on average absorb market liquidity. Such trades are likely driven by information and therefore classified as "informed trading". CS^{liq}_{t+1}, on the other hand, measures the characteristics-adjusted return on mutual fund trades that on average supply market liquidity and hence classified as "liquidity provision". In the extreme case where the fund manager only trades one stock and when the time interval is a minute rather than a quarter, CS^{liq}_{t+1} will then closely resemble the realized spread of Huang and Stoll (1996) which measures the reward to market makers' liquidity provision activities. With quarterly holdings data, CS^{liq}_{t+1} is likely to estimate the true reward for liquidity provision with noise. For example, our procedure only captures liquidity-induced price pressures that persist over the calendar quarter end. To summarize, we decompose the fund CS measure as:

$$\begin{aligned} CS_{t+1} &= CS^P_{t+1} + CS^{adj}_{t+1} + CS^A_{t+1}, \\ CS^A_{t+1} &= CS^{inf}_{t+1} + CS^{liq}_{t+1}. \end{aligned} \tag{4}$$

There are several potential empirical issues associated with the above decomposition. First, not all informed trading is liquidity absorbing especially when the trader is very patient and trading small quantities. When trading large quantities quickly, however, it is extremely hard not to absorb liquidity. As a result, liquidity-absorbing trades are still likely information-driven on average. By missing out informed-trading that is not liquidity absorbing, we are underestimating the benefit from informed-trading rather than overestimating it. Second, not all liquidity absorbing trades are information driven. For example, distressed sales by mutual funds as studied in Da and Gao (2006) and Coval and Stafford (2007) are likely to absorb liquidity but have nothing to do with "mispricing" considerations. Such distressed sales should not drive our results though given that the "informed sale", according to our classification, has a past-one-year return of 25%. In addition, since distress stocks are typically associated with small market cap, their impact will be alleviated as each component of the CS measure is computed using value-weighted average. Most importantly, non-information driven, liquidity-absorbing trades are likely associated with negative CS measures, again resulting in an underestimation of the benefit from informed-trading rather than an overestimation. Third, as mutual funds' trades can only be inferred from changes in mutual fund holdings at quarterly frequency, we would therefore miss out high-frequency turnovers by mutual funds as studied in Kacperczyk, Sialm and Zheng (2007) and Elton et al. (2006).[17] Finally, the classification of informed trading and liquidity provision is done with quarterly data which could also be noisy. These noises should bias us against finding any significant results.

For active funds in our sample, we examine their mutual fund holding changes over two consecutive quarters and categorize them into four groups: (1) "Open" (holdings increase from zero to positive); (2) "Close" (holdings decrease from positive to zero); (3) "Increase" (holdings increase but not from zero) and (4) "Decrease" (holdings decrease but not to zero). For each group, we then compute the average dollar holding change as a percentage of the total dollar holding change of the fund (computed using prices at quarter end); the average order-imbalance measure (defined as the difference between total numbers of buyer-initiated shares brought and total numbers of seller-initiated shares sold divided by total number of shares traded during the quarter, the resulting number is then cross-sectionally demeaned) and the associated t-value.

The results are provided in Table 2. The average order imbalance measure for each trade type tells us whether the trade is on average absorbing liquidity or demanding liquidity. We document

[17] Preliminary analysis suggests that results in our paper are not driven by such "unobservable actions" of mutual funds. We obtain very similar results after removing fund / quarter observations associated with extreme "return gaps" (top and bottom 20%) defined in Kacperczyk, Sialm and Zheng (2007). In addition, the return gap is not significant in explaining CS measure and its component in cross-sectional regressions.

that when fund managers open new positions and close out existing positions, they are likely to absorb market liquidity. In those cases, these trades are likely motivated by large "mispricings" perceived by fund managers who are willing to pay for the price of immediacy. When mutual funds adjust their holdings, they are likely to provide liquidity on average only when they decrease their holdings, consistent with our conjecture that it is easier to provide liquidity on stocks that one currently owns.

Before applying the decomposition to the entire sample of active US equity mutual funds in the next section, we first demonstrate the effectiveness of our decomposition methodology using two specific examples: (1) Dimensional Fund Advisors and (2) a group of domestic index funds.

2.1 Illustrative examples

2.1.1 Dimensional Fund Advisors (DFA)

Dimensional Fund Advisor (DFA) is an asset management firm founded in 1981. Allegedly, the firm does not pick stocks via fundamental analysis. Instead, the firm helps its clients get exposure to certain segments of the asset markets via passive indexing or enhanced indexing. Anecdotal evidence suggests that a subset of the funds managed by DFA create value by systematically providing liquidity to those who want to trade small stocks for non-information related reasons.[18] If it is the case, using our decomposition procedure, one would expect to find a positive liquidity provision component in DFA's CS measure and an informed trading component close to zero. Of course, since we examine one specific fund over a limited time span, the statistical significance could be rather weak.

We examine the quarterly stock holdings of DFA's flagship fund, US Micro Cap Portfolio, during the period from 1983 to 2004 and decompose its CS measure. The results are provided in Table 3. The overall CS measure for the fund is 36.1 bps per quarter but not statistically significant (t-value = 1.72), indicating that the fund does not seem to possess any ability to select stocks that outperform those with similar characteristics. As expected, the largest component of the overall CS measure is due to liquidity provision (20.5 bps per quarter) which is significant at 10% level (t-value = 1.84). In contrast, the informed trading component is very close to zero and statistically

[18] See the case studies by Keim (1999) and Cohen (2002).

insignificant, which is consistent with what firm's investment policy claims.

2.1.2 Index funds

Since the majority of index funds are formed to track the market index or other broad indices with the objective of minimizing tracking errors, we do not expect them to have a large CS measure. Index funds are most likely to trade during index rebalancing and demand liquidity in those trades (see Blume and Edelen, 2004). These trades would be incorrectly classified as "Informed Trading" within our decomposition framework, and the Informed Trading component, if different from zero, is likely to be negative. It is therefore less appropriate to apply the decomposition to index funds. For that reason we will be focusing only on actively managed funds for the remaining parts of the paper. Nevertheless, examining index funds provides another opportunity to test the validity of our decomposition approach.

We identify the index funds by their fund names recorded in CDA/Spectrum $S12$ mutual fund holding database. During the period from 1983 to 2004, there are about 11 domestic index funds identified each quarter on average from the holding database, starting from 1 fund each quarter in 1983 to about 25 funds each quarter after 2000. Using their stock holdings, we apply our decomposition to each fund and the results are then equally-weighted across funds during every quarter. The results are again presented in Table 3. The overall CS measure for index funds as a group is almost exactly zero. The index fund group has a positive although not significant CS^P component of about 25 bps per quarter on average (t-value = 0.93), which may be from security lending fees. In addition, the index funds on average make some profit (although not significant) from providing liquidity, as evident from a positive CS^{liq} component of about 6 bps per quarter (t-value=0.36). Interestingly, the positive CS^P and CS^{liq} are offset by a negative Informed Trading component (CS^{inf}= -35 bps) which is statistically significant, indicating a sizable price for liquidity paid by the index funds for trades that arise due to index rebalancing, new money flowing in, and redemptions.

3 Decomposing Stock Selection Skills for Active Fund Managers

We implement the decomposition for all US domestic active equity funds in our sample. To examine the relative importance of each component of the total CS measure, we carry out a variance decomposition exercise. The details are provided in Appendix B. In a nutshell, the variance decomposition delineates how much the cross-sectional variation in the total CS measure can be attributed to the cross-sectional variation in each of its four components. The results are reported in Table 4 for the full sample of all active US equity managers and across three style-subsamples. Overall, the passive component (CS^P) explains about 57% of the total cross-sectional variation in the total CS measure. The informed trading component (CS^{inf}) explains about 37% of the total variation, more important than the liquidity provision component (CS^{liq}) which explains slightly more than 8%. In addition, CS^{inf} becomes relatively more important for growth-oriented funds while CS^{liq} becomes relatively more important for income-oriented funds.

The average magnitude of each component is summarized in the top portion of Table 6. Overall, the active fund managers seem to possess some stock selection skill that requires trading with the order imbalance in the market. The average CS measure is 23.5 bps per quarter (t-value = 1.91), indicating stocks selected by the fund managers outperform those with similar characteristics. Out of the 23.5 bps, 13.9 bps come from the passive "buy-and-hold" strategy and 14.2 bps come from stocks recently traded by the funds. The adjustment component is small (-1.9 bps) in absolute term but significant, potentially driven by fund flow to managers with skills as empirically documented by Chevalier and Ellison (1997) among others and theoretically analyzed by Berk and Green (2004).[19] Finally, although both the informed trading component (CS^{inf}) and the liquidity provision component (CS^{liq}) are positive, neither is significant.

3.1 Stock selection and Private Information

As informed trading adds value through superior information-processing skills, value enhancing informed trading is more likely to take place in stocks during times when they are associated with more information events. To identify the occurrence of information events, we first make use of the

[19] When managers have skill (CS^P is likely to be positive), fund inflow is more likely ($B > S$); When managers have no skill (CS^P is likely to be negative), fund outflow is more likely ($S > B$). Both effects lead to a negative CS^{adj} as in equation (2).

Probability of Informed Trading measure (PIN), which is a market microstructure based measure developed by Easley, Kiefer, O'Hara and Paperman(1996) and Easley, Kiefer and O'Hara (1997). In their model, there are two types of traders: informed traders and uninformed traders. In the absence of information events, only uninformed traders trade (primarily for liquidity reasons) and the order is equal likely to be a Buy or Sell, resulting in an order imbalance measure close to zero on average and a low PIN measure. On the other other hand, when there are significant information events and informed traders also trade, there will be large amount of Buy orders *or* Sell orders (depending on the nature of the information), resulting a large order imbalance and a high PIN measure.[20] Empirically, PIN decreases with size and analyst coverage but increases with bid-ask spread, insider and institutional ownership, consistent with it being a reasonable measure of private information event. Recently, PIN measure has been widely used in the empirical finance literature, for instance, in Brown, Hillegeist and Lo (2004), Vega (2006), Bharath, Pasquariello and Wu (2006) and Chen, Goldstein and Jiang (2006).

To the extent that PIN indeed captures the frequency and intensity of information events, we expect that funds trading high-PIN stocks to have a large and significant informed trading component (CS^{inf}), since the benefit from their information must be higher than the cost for demanding liquidity for them to initiate the trades (see Grossman and Stiglitz, 1980). Funds trading high-PIN stocks may also trade against the order imbalance. The return on these trades will be considered as the liquidity provision component. On one hand, these funds may face the danger of trading against informed traders. On the other hand, by judiciously choosing their trades, they could potentially benefit from the price impact working to their advantage, which could be sizable for high-PIN stocks. The net effect of the two will determine the sign and magnitude of the liquidity provision component for these funds. Funds trading low-PIN stocks are less likely to encounter informed traders when they trade. Consequently, when they trade against the market order imbalance, they are more likely to benefit from the price impact, resulting in a positive liquidity provision component. When they initiate the trade however, they suffer from the price impact which may outweigh the information advantage, and informed trading component will as a result be negative.

To estimate PIN, we use the tick-by-tick transaction data for each quarter from 1983 to 2004

[20] A more detailed description of the PIN measure and its estimation procedure is contained in the Appendix C.

using the entire three-month data to ensure the precision of estimation. A breakdown of our stock sample is provided in Panel A of Table 5. Overall, we have on average 4110 stocks with PIN measures in a quarter. Due to data availability from ISSM, NASDAQ stocks enter the sample in 1987 and account for a large portion of the sample. The mean of PIN measures in our sample is 25.8% with an associated standard deviation of 12.1%. The correlations between PIN and other stock characteristics are tabulated in Panel B of Table 5. Consistent with Easley, Hvidkjaer and O'Hara (2002), we find that high-PIN stocks are likely to be smaller and less liquid stocks. There is also some positive correlation between PIN and book-to-market ratio.

In each quarter and for each fund, we then compute a $trade\_PIN$ variable by value-weighting the PIN of stocks traded by the fund during the quarter using the dollar value of the trade. Specifically, we compute $trade\_PIN$ for the j-th mutual fund at the end of quarter t in our sample as

$$trade\_PIN_{j,t} = \frac{\sum_{i=1}^{N} PIN_{i,t} \times d_{i,j}}{\sum_{i=1}^{N} d_{i,j}},$$

where $PIN_{i,t}$ is the estimated PIN measure of the i-th stock traded by the mutual fund j during quarter t, and $d_{i,j}$ is the absolute dollar value (using the stock price at the end of the quarter) of the holding change during quarters t as reported by the mutual fund j. Intuitively, funds that buy or sell high PIN stocks would have higher $trade\_PIN$ measures.

We then sort all funds in our sample into deciles at the end of each quarter from 1983 to 2004 according to their $trade_PIN$s and decompose the CS measure within each decile. Results are presented in Table 6. The CS measure and its components are winsorized at 1^{st} and 99^{th} percentiles to alleviate the effect of outliers.

Several interesting patterns emerge from this table. First, funds trading high-PIN stocks (High $trade\_PIN$) outperform those trading low-PIN stocks (low $trade\_PIN$) by almost 53 bps per quarter on the dimension of stock selection. The 53 bps spread is highly significant with a t-value of 2.87. We also find similar results using actual after-fee mutual fund returns from the CRSP mutual fund database. The after-fee mutual fund return spread between the two deciles is 50 bps per quarter with a t-value of 3.27 after four-factor risk adjustment, which would suggest that window-dressing by mutual fund does not drive our result as such activity only improves return on "paper."

Second, the spread is mainly driven by high-$trade\_PIN$-funds with an average CS measure of almost 50 bps (t-value = 2.70). In contrast, the CS measure of the low-$trade\_PIN$-fund is small and negative (-2.9 bps). Third, a large part of the CS measure for high-$trade\_PIN$-funds comes from active trading during the quarter (CS^A = 31.2 bps with a t-value of 2.83). Fourth, although both the informed trading component (CS^{inf}) and the liquidity provision component (CS^{liq}) are positive for high-$trade\_PIN$-funds, only the the informed trading component is significant (20.4 bps with a t-value of 2.25) and its size is twice that of the liquidity provision component (10.4 bps). This is consistent with our conjecture. When skillful managers absorb liquidity trading high-PIN stocks, they are likely to possess valuation-relevant information and therefore make money from informed trading. For them, the added cost of demanding immediacy in the market must be smaller than the benefit from superior information. In terms of liquidity provision, not all of them can perform as well as DFA. As a result, although the liquidity provision component is positive on average, it is much smaller and not significant, potentially due to the possibility of trading against informed traders.

Finally, low $trade\_PIN$-funds, having almost zero stock selection skill on average, seem to possess some skill in liquidity provision. The liquidity provision component (16.2 bps) is significant (t-value = 2.57). This is again consistent with our conjecture. When fund managers trade low-PIN stocks, they are likely to trade with uninformed traders. When they trade against market order imbalance, they are likely to make money by providing the needed liquidity. The positive liquidity provision component is partly offset by a negative informed trading component, resulting in a close-to-zero CS measure.

Although PIN is motivated in a structural model of informed trading, the empirical estimates should not be taken too literally. As Hasbrouck (2007) points out, PIN by construction is a meaningful measure of order flow one-sidedness. Independent of specific assumptions imposed on the trade arrival processes, frequent and large information events would result in order imbalances. Consistent with this interpretation, Aktas, Bodt, Declerck and Oppens (2007) and Kaul, Lei and Stoffman (2007) consider an approximate PIN measure: relative order imbalance (rel_OIB), defined as:

$$rel\_OIB = \frac{E\left[|B-S|\right]}{E\left[B+S\right]},$$

where B and S denote the daily number of buyer-initiated trades and seller-initiated trades, respectively. Like PIN, rel_OIB is also a number between 0 and 1 and can therefore be interpreted as a probability. Aktas et al. (2007) show that rel_OIB is exactly equal to PIN on a daily basis and serves as a very good approximation during a longer time window.[21] rel_OIB is clearly a measure of order flow one-sidedness. Compared to PIN, it is relatively easy to compute and does not suffer from the problem of poor convergence during the maximum likelihood estimation of PIN. On the other hand, rel_OIB is sensitive to a few extreme large daily order imbalance values in the sample whereas such outliers have much less impact on the estimated PIN value.

Therefore, in order to examine the robustness of our empirical findings we repeat the entire exercise by replacing PIN with rel_OIB. We exclude stocks that trade less than 15 days within a quarter and estimate rel_OIB using simple daily average within each quarter. We first verify that rel_OIB is an reasonable approximation of PIN. The average cross-sectional correlation between these two measures is above 0.75. In addition, we are able to compute rel_OIB for a larger number of stocks since we avoid the convergence problem associated with PIN. The decomposition results within rel_OIB-sorted fund decile can be found in Table 7. The main results are almost identical qualitatively using the alternative PIN measure.

We also consider a second measure of the degree of private information events, *theta* (θ), the information asymmetry component of the spread as proposed in Madhavan, Richardson and Roomans (1997).[22] *Theta* is computed for each stock during each quarter. The resulting *theta* is then used to replace PIN in calculating a $trade\_theta$ for each fund each quarter. At the end of each quarter from 1983 to 2004, we sort all mutual funds in our sample into deciles according to their $trade_theta$s and decompose the CS measure within each decile. As usual, the CS measure and its components are winsorized at 1st and 99th percentiles to alleviate the effect of outliers. The results are presented in Table 8. Our results remain unchanged qualitatively.

How can we discern which funds are more likely to trade high-PIN stocks? We tabulate the average fund-level characteristics across $trade\_PIN$-sorted fund deciles in Panel A of Table 9.

[21] See Appendix C for a brief discussion on this issue.

[22] A more detailed description of the θ measure is contained in the Appendix C.

All characteristics are winsorized at 1^{st} and 99^{th} percentile to alleviate the effect of outliers. We find that high-$trade\_PIN$ funds are typically associated with smaller fund size, smaller fund age, higher expense ratios, higher percentage fund inflow. In addition, high-$trade\_PIN$ funds tend to hold more stocks, smaller and more illiquid stocks. Their stock holding as a percentage of total number of share outstanding is also higher on average. These patterns are confirmed in Panel B of Table 9 which reports the correlations among these variables. Finally, their investment style more likely belongs to the AGG or Growth categories. In contrast, the investment style of the low-$trade\_PIN$ funds leans more towards the GNI spectrum.

3.1.1 Stock selection and momentum trading

Grinblatt, Titman and Wermers (1995) document that the majority of mutual funds use momentum as stock selection criterion and thus the momentum effects can significantly influence the mutual fund performance. Panel A of Table 9 indeed shows that funds trading high-PIN stocks hold more recent winners than funds trading low-PIN stocks, resulting in a higher $fund\_mom$ on average. A natural question arises: could the difference in the CS measures between funds trading High and Low PIN stocks be driven by the momentum effect? We believe that the answer is *no* for several reasons. First, the CS measure and its components throughout the paper are computed after adjusting for book-to-market, size and momentum characteristics following Daniel, Grinblatt, Titman and Wermers (DGTW, 1997). Second, when we regress the CS measure on several fund characteristics in a cross-sectional regression in the next subsection, we find $fund\_mom$ to be insignificant while $trade\_PIN$ is still highly significant, confirming that the large CS measure associated with funds trading high-PIN is not driven by the momentum effect. Finally, we directly examine the average past return characteristics of stocks bought, sold and held by the funds separately in Table 10. Specifically, in each quarter and for each fund, we first compute the value-weighted average past one-year return of stocks in the "Buy" portfolio (stocks recently bought by the fund), the "Sell" portfolio (stocks recently sold by the fund) and the "Hold" portfolio (stocks held by the fund throughout the quarter). These past returns are then averaged across funds in the same $trade\_PIN$ decile and across time. Although high $trade\_PIN$ funds do seem to buy more recent winners than low $trade\_PIN$ funds (the average past one year return in the "Buy" portfolio is 34.3% for high $trade\_PIN$ funds *vs.* 20.9% for low $trade\_PIN$ funds), they are selling more extreme recent winners at the same time (the average past one year return in the "Sell" portfolio is 46.6% for high $trade\_PIN$ funds) and therefore are not "momentum traders" in the traditional sense. In addition, funds in $trade\_PIN$ deciles 7 to 9 seem to buy or hold even more winners than funds in the top $trade\_PIN$ decile. If the momentum effect drives the high CS measure, we would expect funds in $trade\_PIN$ deciles 7 to 9 to have higher CS measures on average. That is clearly not the case as in Table 10.

3.2 Informed trading, liquidity provision and fund characteristics

To examine the relation between fund characteristics and the CS measures, we use a Fama-MacBeth (1973) cross-sectional regression approach. Specifically, we regress the next quarter CS measure and its components on several fund-level characteristics during each quarter from 1983 to 2004. All right side variables are measured as deviations from their corresponding cross sectional means, standardized to have unit variance, and winsorized at 1% and 99% to alleviate the effect of outliers. Fund momentum denotes the value weighted return on the stocks help by the fund at the end of each quarter during the preceding 12 months, (standardized to have zero mean and unit variance in the cross section of all funds. All other variables are self explanatory. The effect of a fund's style is captured by two dummy variables that correspond to "Growth" and "AGG", respectively. All explanatory variables (except for the style dummy variables) are cross-sectionally demeaned and standardized so the corresponding coefficients can be interpreted as the impact on return of one standard deviation change in the variable. In addition, the regression intercept can be interpreted as the average effect of having a "GNI" fund style. Finally, the regression coefficients are averaged across time and the associated t-values are computed using Newey-West correction with lead / lag terms of 8 quarters to account for the autocorrelations in the error terms. The regression results are reported in Table 11.

When we regress the total CS measure on the fund characteristics, we find $trade\_PIN$ to be significant even in the presence of many other fund-level characteristics, indicating that the difference in stock selection skill between funds trading high-PIN stocks and those trading low-PIN stocks is not entirely driven by other correlated fund characteristics. In addition, the significance of $dummy\_AGG$ means that funds with an "Aggressive Growth (AGG)" investment style are better in selecting stocks, confirming earlier findings by Daniel, Grinblatt, Titman and Wermers

(1997). We then move on to the two particular components of the total CS measures: the informed trading component (CS^{inf}) and the liquidity provision component (CS^{liq}). Interestingly, the fund-characteristics associated with informed trading and liquidity provision are quite different. When we regress CS^{inf} on the fund characteristics, we find $trade\_PIN$ to be even more significant, indicating that the positive relation between stock selection skill and high $trade\_PIN$ is likely driven by informed trading. In addition, $dummy\_AGG$ remains to be significant, indicating that informed trading is more prevalent in funds with an "Aggressive Growth (AGG)" investment style. In contrast, when we regress CS^{liq} on the fund characteristics, different patterns emerge. First, $trade\_PIN$ is now negatively related to CS^{liq} (although not significantly). Second, intercept and age are significant, indicating that younger funds and funds with "Growth and Income (GNI)" investment styles are likely to be rewarded more via liquidity provision.

3.3 Persistence of the informed trading and liquidity provision component

We examine the persistence in the CS measure and its component. At the end of each quarter from 1983 to 2004, we sort funds into deciles based on their CS measure during the quarter. We then tabulate the average CS measure across the deciles during the next quarter. If the manager's stock selection skill is persistent, we would expect funds with the highest CS measures this quarter to continue to have significantly higher CS next quarter relative to funds with the lowest CS measures. We repeat the sorting exercise for the components of the CS measure: CS^P, CS^{inf} and CS^{liq}. The results are reported in Table 12. Overall, there is weak evidence of persistence in the active fund managers' stock selection skills. The average CS measure of funds in the highest CS-decile during the prior quarter is 73 bps higher than that of funds in the lowest CS-decile, although the spread is only marginally significant at 10% level. Interestingly, when we look at the components of CS, only the informed trading component (CS^{inf}) seems to be persistent. By isolating the informed trading trading component which is persistent, our decomposition could be used to better predict mutual fund performance in the future.

The insignificant persistence in the liquidity provision may be consistent with the notion that liquidity-based trading at quarterly frequency is episodic since the opportunity of low-frequency liquidity provision is sporadic. For example, Coval and Stafford (2007) investigates forced mutual funds transactions due to fund inflows and outflows, and identify economically important but statistically noisy profits when market participants are able to trade against the mutual funds "fire" sales and purchases.

4 Conclusion

The traditional approach to portfolio performance evaluation is to decompose the skill of a portfolio manager into two components: Security Selection and Marketing Timing. In this paper we suggest a further decomposition of the former based on whether the portfolio manager's trades demand liquidity ("informed trading") or provide liquidity ("liquidity provision"). We develop a method for that decomposition based on the composition of the portfolio holdings of a mutual fund. We illustrate the use of our decomposition method by empirically examining the the stock selection ability of managed mutual funds.

Using the quarterly mutual fund holdings data for the period from 1983 to 2004 and detecting private information events using both Probability of Informed Trading (PIN, Easley et al., 1996) and information asymmetry component of the spread (Madhavan et. al., 1997), we find that value enhancing informed trading is more likely in stocks during times when they are associated with more information events. In contrast, liquidity provision is more likely to add value for stocks associated with few information events and little adverse selection risk. Further, we find that the informed trading component is more significant for funds with a growth-oriented investment objective and is persistent. In contrast, the liquidity provision component, on the other hand, is significant mostly for younger funds with an income-oriented investment objective and is not persistent. Given the difference between informed trading and liquidity provision activity, our decomposition would further improve the evaluation of mutual fund managers' skill and help to better predict funds' performance in the future.

The empirical implementation of our decomposition is subject to two limitations. First, since we observe mutual fund holdings only at quarterly intervals, we are able to capture only a part of the value added by the fund manager through liquidity and informated trading. For example, at quarterly frequency, we are only able to examine persistent liquidity events. Second, PIN and the information asymmetry component of bid-ask spreads are imperfect measures of the frequency and intensity of private information events. Bearing these challenges to our empirical exercise, we have made the first attempt to bring both informed trading and liquidity provision into the evaluation of mutual funds stock selectivity. As the availability of high frequency fund transaction data, our procedure in theory could be used to evaluate the manager's contribution on these two dimensions with greater precision.[23]

[23] As a practical matter, this may not be an issue for fund of funds and large institutional investors – they get almost daily reports of the holdings of the managers who manage their funds.

Appendix A: A Numerical Example for the Decomposition of Mutual Fund Stock Selection Skill

Assume there are six stocks (A, B, C, D, E and F). A mutual fund's holdings on these stocks at the end of quarter $t-1$ (N_{t-1}) and t (N_t), stock prices at the end of quarter t (P_t) and the characteristics-adjusted stock returns during quarter $t+1$ ($R_{j,t+1} - BR_{t+1}(j,t)$) are summarized in the following table:

Stock	N_{t-1}	N_t	P_t	$R_{j,t+1}-BR_{t+1}(j,t)$
A	2	1	10	−3%
B	2	0	15	−2%
C	2	2	20	−1%
D	2	2	25	1%
E	2	3	30	2%
F	0	2	35	3%

The "Hold", "Buy" and "Sell" are then defined by their holdings N_t^H, N_t^B and N_t^S:

Stock	$N_t^H = \min(N_{t-1}, N_t)$	$N_t^B = N_t - N_t^H$	$N_t^S = N_{t-1} - N_t^H$
A	1	0	1
B	0	0	2
C	2	0	0
D	2	0	0
E	2	1	0
F	0	2	0
Value	$H_t = 160$	$B_t = 100$	$S_t = 40$

The portfolio values H_t, B_t and S_t are determined using the prices at the end of quarter t (P_t). Notice $B_t > S_t$, and the difference is likely financed by fund inflows, or a decrease in cash position or sale of other non-stock assets held by the fund. The "Hold", "Buy" and "Sell" can be treated as three separate funds whose CS measures can be computed using equation (1) and holdings as:

	"Hold"	"Buy"	"Sell"
CS	$CS_{H,t+1}$= 0.63%	$CS_{B,t+1}$= 2.70%	$CS_{S,t+1}$= −2.25%

With the above information, equation (2) then decomposes the total CS measure into three components:

CS_{t+1}	CS^P_{t+1}	CS^A_{t+1}	CS^{adj}_{t+1}
1.42%	0.05%	1.49%	−0.12%

If we further assume that the fund traded B and F in the same direction as the aggregate order imbalance and traded A and E against the direction of aggregate order imbalance, then equation (3) further decomposes the active component (CS^A_{t+1}) into a "informed trading" component (CS^{inf}_{t+1}) and a "liquidity provision" component (CS^{liq}_{t+1}):

CS^A_{t+1}	CS^{inf}_{t+1}	CS^{liq}_{t+1}
1.49%	1.11%	0.38%

Appendix B: Variance Decomposition of the "Characteristic Selectivity" (CS) Measure

Empirically, we decompose the total "Characteristic Selectivity" (CS) measure (DGTW, 1997) into four components:[24]

$$CS = CS^P + CS^{adj} + CS^{inf} + CS^{liq}.$$

Consequently, we have

$$var(CS) = cov(CS, CS^P) + cov(CS, CS^{adj}) + cov(CS, CS^{inf}) + cov(CS, CS^{liq}),$$

where $var(\cdot)$ and $cov(\cdot)$ are the cross-sectional variance and covariance, respectively. Dividing both sides of the above equation by $var(CS)$, we then have

$$1 = \beta_P + \beta_{adj} + \beta_{inf} + \beta_{liq}.$$

[24] For simiplicity of notation, we omit the time subscript t and fund superscript i.

The term $\beta_{(\cdot)}$ then measures the contribution of component $(\cdot)$ to the cross-sectional variations of CS. The sum of the contribution from the four components is equal to one by construction. β can be measured by regression. For instance, β_P is estimated by regressing CS^P on CS cross-sectionally. Empirically, we have a panel data of cross-sectionally demeaned CS, CS^P, CS^{adj}, CS^{inf} and CS^{liq}. To estimate β, we run a Weighted Least Squares (WLS) regression. In practice, this means deflating the data for each fund-quarter by the number of funds in the corresponding cross-section (see Vuolteenaho, 2002).

Appendix C: Measures of Private Information Events — A Brief Description

Easley and O'Hara, along with their coauthors, in a series of papers develop this measure to capture the probability of information-based trading. Let α denote the probability that an information event occurs; δ denote low value of underlying asset, conditioning on the occurrence of informational event; μ is the rate of informed trade arrivals; ϵ_b is the arrival rate of uninformed buy orders; ϵ_s is the arrival rate of uninformed sell orders. Easley, Hvdkjaer and O'Hara (2002) propose the following MLE estimation to estimate the parameter vector $\Theta \equiv \{\alpha, \mu, \epsilon_b, \epsilon_s, \delta\}$

$$\begin{aligned} L\left(\Theta|B,S\right) &= \left(1-\alpha\right) e^{-\epsilon_b}\frac{\epsilon_b^B}{B!}e^{-\epsilon_s}\frac{\epsilon_s^S}{S!} \\ &\quad +\alpha\delta e^{-\epsilon_b}\frac{\epsilon_b^B}{B!}e^{-(\mu+\epsilon_s)}\frac{\left(\mu+\epsilon_s\right)^S}{S!} \\ &\quad +\alpha\left(1-\delta\right)e^{-(\mu+\epsilon_s)}\frac{\left(\mu+\epsilon_b\right)^B}{B!}e^{-\epsilon_s}\frac{\epsilon_s^S}{S!} \end{aligned} \tag{5}$$

where B and S represent total buy trades and sell trades for the day respectively. Given the above specifications, the probability of information-based trade, PIN, is

$$PIN = \frac{\alpha\mu}{\alpha\mu + \epsilon_b + \epsilon_s}. \tag{6}$$

With some independence assumptions across trading days, the likelihood function (5) becomes

$$L\left(\Theta|\left(B_i, S_i\right)_{i=1}^{i=N}\right) = \prod_{i=1}^{N} L\left(\Theta|B_i, S_i\right). \tag{7}$$

The problem with estimation of PIN measure is that later years (since 2001), the number of buy and sell orders becomes extremely large, particularly for some NASDAQ stocks. One way to solve this problem, as in Vega (2006), is to impose the constraint that the arrival rates of informed and uninformed orders are the same,

$$\epsilon_b = \epsilon_s = \epsilon, \tag{8}$$

hence we estimate a modified version of (5),

$$L\left(\Theta|B,S\right) = (1-\alpha)\, e^{-2\epsilon}\frac{\epsilon^{B+S}}{B!S!} + \alpha\delta e^{-(\mu+2\epsilon)}\frac{\epsilon^{B}\left(\mu+\epsilon\right)^{S}}{B!S!} + \alpha\left(1-\delta\right) e^{-(\mu+2\epsilon)}\frac{\epsilon^{S}\left(\mu+\epsilon\right)^{B}}{B!S!} \tag{9}$$

and consequently, the probability of informed trading, PIN, is

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\epsilon}. \tag{10}$$

It is interesting to note that the probability that an information event occurs (α) and the rate of informed trade arrivals (μ) enter PIN as a product term ($\alpha\mu$). Although α and μ may be individually estimated rather imprecisely, since estimation errors in these two parameters are usually strongly negatively correlated, the resulting PIN estimate is quite precise. In addition, the variation in α and μ are offsetting, making PIN a much stable measure bounded between 0 and 1. This is an important reason why PIN is chosen over alternative measures for private information such as the price non-synchronicity measure (see Roll, 1988 and Morock, Yeung and Yu, 2000, Durnev, Morck, Yeung and Zarowin, 2003 and Durnev, Morck and Yeung, 2004) and the adverse-selection component of bid-ask spread (Glosten and Harris, 1988 and Huang and Stoll, 1996).

In the economy of Easley et al. (2001), the total number of trades $B+S$ and the order imbalance $B-S$ are related to parameters of the model. as:

$$\begin{aligned} E\left[B+S\right] &= \alpha\mu + 2\epsilon, \\ E\left[B-S\right] &= \alpha\mu(1-2\delta). \end{aligned}$$

Since each day is either a good day ($\delta = 0$), a bad day ($\delta = 1$), or a no-event day ($\alpha = 0$), the expected daily absolute OIB is then:

$$E\left[|B-S|\right]=\alpha\mu.$$

Aktas, Bodt, Declerck and Oppens (2007) and Kaul, Lei and Stoffman (2007) show that a relative order imbalance measure $rel\_OIB = E\left[|B-S|\right]/E\left[B+S\right]$ serves as a very good approximation to PIN. In fact, on a daily basis, rel_OIB is equivalent to PIN.

In addition to causing large order imbalance, informed-trading will also force the market maker to increase the bid-ask spread. In the structural model of intra day trading costs proposed by Madhavan et. al. (1997), the price change can be captured by:

$$p_t - p_{t-1} = (\phi+\theta)x_t - (\phi+\rho\theta)x_{t-1} + u_t$$

Here x_t is the sign of the order flow (1: trade at ask, -1: trade at bid, 0: trade between bid and ask), ϕ is the market maker's cost of supplying liquidity, ρ is the autocorrelation of the order flow, and θ captures the sensitivity of beliefs to unexpected order flows or the degree of private information. θ is therefore known as the information asymmetry component of the bid-ask spread and serves as an alternative measure of private information events. ϕ, ρ and θ will be jointly estimated with transaction level data using GMM on a quarterly basis.

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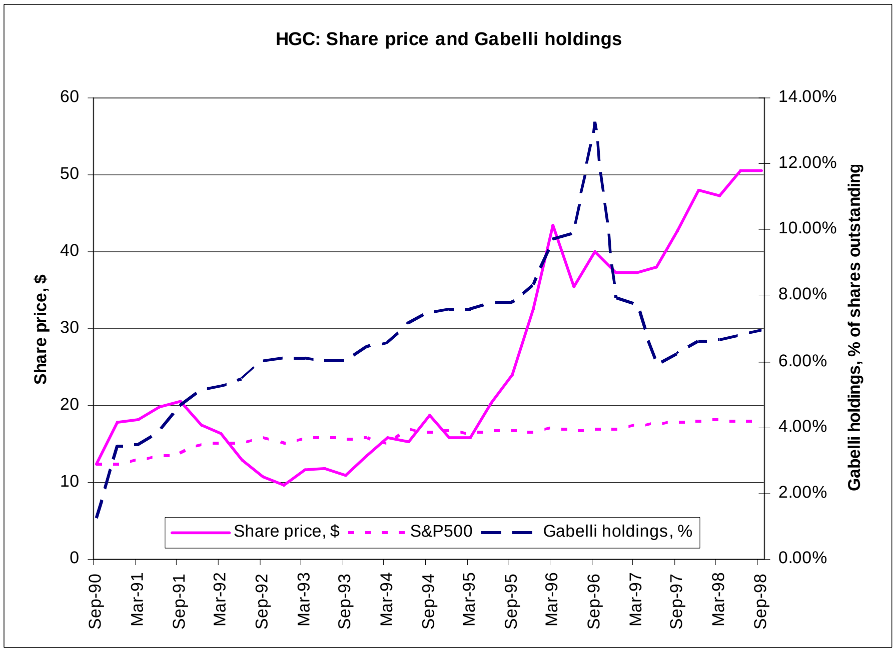
Figure 1: Share price and mutual fund holdings

Figure 1 plots the share price of Hudson General Corp (HGC) and Gabelli Fund's holdings of HGC (as a percentage of total number of shares outstanding) from September 1990 to September 1998. Figure 2 plots the share prices of Starbucks (SBUX) from June to December 2005 (price is normalized so that the end-of-July-price is 1) and Putnam Voyager Fund's holdings of Starbucks (as a percentage of total number of shares outstanding) at the end of June, September and December.

A: Share price of Hudson General Corp (HGC) and Gabelli's Holdings



B: Share Price of Starbuck (SBUX, normalized) and Putnam Voyager Fund's Holdings

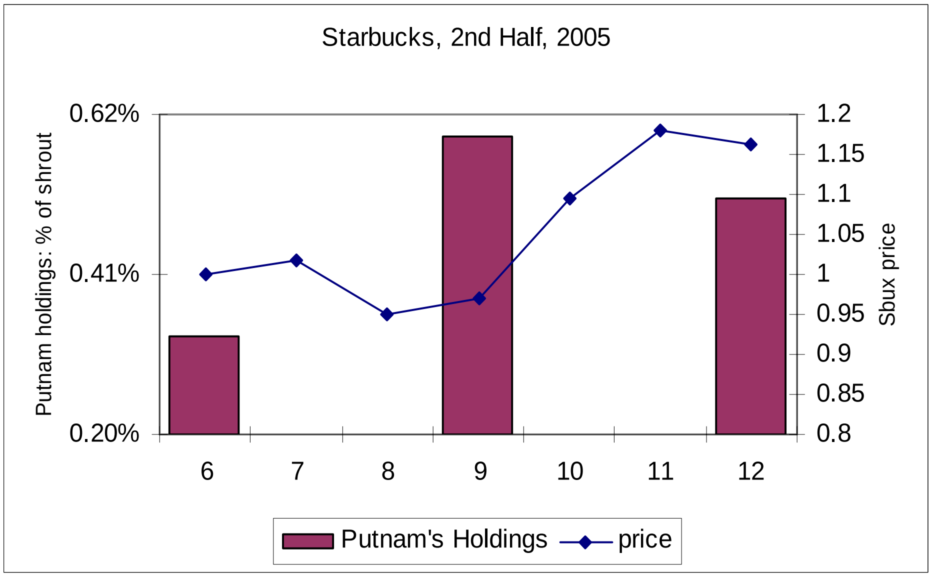


Table 1: Breakdown of mutual fund sample over time

We report the breakdown of our mutual fund sample by the self-reported investment objectives. Consistent with prior literature on actively managed mutual funds, we exclude all index funds, lifecycle mutual funds, bond funds, hybrid funds, sector funds, and international funds. We only keep funds that are self-reported as aggressive growth (AGG), growth (GROWTH) or growth and income (GNI). To ensure our sample of mutual funds are relatively active, we also exclude fund / quarter observations with quarterly turnover less than 10% or if the fund trades less than 10 during that quarter. Finally, we only include fund / quarter observations for which the fund holdings at the end of previous quarter are also available so that holding changes can be computed over consecutive quarters. The CDA/Spectrum mutual fund holding data are matched to CRSP Mutual Fund data via the MFLINKS database.

year	# of funds per qtr	AGG	GROWTH	GNI
1983	132	35	57	40
1984	163	38	73	52
1985	201	44	98	59
1986	234	43	125	66
1987	291	59	156	76
1988	328	73	173	82
1989	283	57	151	75
1990	293	59	157	77
1991	327	73	172	82
1992	397	84	217	96
1993	438	95	242	102
1994	353	65	208	80
1995	353	59	194	100
1996	468	54	271	142
1997	557	64	337	157
1998	913	88	586	238
1999	1291	125	856	310
2000	1843	190	1182	472
2001	1431	159	913	359
2002	1775	201	1106	468
2003	1776	181	1116	480
2004	1459	130	911	419
All	696	90	423	183

Table 2: Type of mutual fund trades and the average order imbalances

For each fund in our sample, we examine their holding changes over two consecutive quarters and categorize them into four groups: (1) "Open" (holdings increase from zero to positive); (2) "Close" (holdings decrease from positive to zero); (3) "Increase" (holdings increase but not from zero) and (4) "Decrease" (holdings decrease but not to zero). For each group, we report the average dollar holding change as a percentage of the total dollar holding change of the fund (computed using prices at quarter end), the average order-imbalance measure (defined as the difference between total numbers of buyer-initiated shares brought and total numbers of seller-initiated shares sold divided by total number of shares traded during the quarter, the resulting number is then cross-sectionally demeaned) and the associated *t*-value. The sampling period is from 1983 to 2004.

trade type	ALL			AGG			GROWTH			GNI		
	% of all trades	oimb	t-value	% of all trades	oimb	t-value	% of all trades	oimb	t-value	% of all trades	oimb	t-value
Open	30.6%	0.31%	4.09	34.5%	0.36%	3.19	31.2%	0.14%	1.61	27.7%	0.61%	7.21
Close	26.7%	-0.27%	-4.73	30.8%	-0.15%	-1.32	27.4%	-0.26%	-3.63	24.0%	-0.30%	-3.75
Increase	22.8%	0.48%	9.27	17.5%	0.48%	5.86	22.0%	0.55%	8.37	26.4%	0.37%	5.07
Decrease	19.9%	1.27%	18.06	17.3%	1.69%	14.51	19.4%	1.34%	15.67	21.9%	0.84%	11.17

Table 3: Decomposition of the mutual fund "Characteristics selectivity" (CS) measure for DFA US Micro-Cap fund and index funds as a group

We provide two examples to illustrate the decomposition of the mutual fund stock selection skill. We decompose the mutual fund "Characteristics selectivity" (CS) measure (Daniel et al., 1997) for DFA US Micro-Cap fund (FUNDNO=16500 in CDA/Spectrum S-12 mutual fund holding database) and Index funds a group (fund whose name contains any of the following: "INDEX", "INDE", "INDX", "S&P", "DOW JONES", "MSCI" or "ISHARE"). Specifically, the CS measure is decomposed into:

$$CS = CS^{P} + CS^{adj} + CS^{inf} + CS^{liq},$$

Where CS^{P} is the passive component; CS^{adj} is an adjustment component due to fund inflows; CS^{inf} and CS^{liq} are the informed trading and liquidity provision components, respectively. The sampling period is from 1983 to 2004. *t*-values associated with the average measures are reported in *italic*s.

	Total CS (=1+2+3)	Passive CS^{P} (1)	Adj CS^{adj} (2)	Active CS^{A} (3=3a+3b)	Info trading CS^{inf} (3a)	Liquidity Prov CS^{liq} (3b)
DFA US Micro-Cap:						
Alpha (bps)	36.1	19.3	-4.2	21.0	0.5	20.5
t-value	*1.72*	*0.89*	*-0.64*	*1.30*	*0.06*	*1.84*
Index Funds:						
Alpha (bps)	0.0	24.9	3.2	-28.1	-34.6	6.4
t-value	*0.00*	*0.93*	*0.50*	*-1.11*	*-2.19*	*0.36*

Table 4: Variance Decomposition of the *CS* measure

This table reports the percentage of total cross-sectional variation in the total "Characteristic Selectivity" (*CS*) measure (DGTW, 1997) explained by its four components: the passive component (CS^P), the adjustment component (CS^{adj}), the informed trading component (CS^{inf}) and the liquidity provision component (CS^{liq}) in a variance decomposition framework outlined in the paper. We perform the variance decomposition on the full sample and on each style-subsample. The *t*-values associated with the percentages are reported in *italic*s, using the weighted least squared (WLS) method. The sampling period is from 1983 to 2004. Details on the variance decomposition can be found in Section 2 and Appendix A of the paper.

Passive CS^P	Adj CS^{adj}	Info trading CS^{inf}	Liquidity Prov CS^{liq}
All			
56.8%	-2.5%	37.2%	8.4%
127.2	*-15.3*	*120.9*	*24.4*
Aggressive Growth (AGG)			
52.1%	-1.0%	44.9%	4.0%
44.7	*-2.7*	*55.2*	*4.2*
Growth (Growth)			
55.7%	-3.0%	37.0%	10.2%
96.0	*-14.9*	*95.0*	*22.3*
Growth and Income (GNI)			
54.1%	-2.2%	37.0%	11.1%
56.8	*-5.4*	*55.9*	*16.6*

Table 5: Descriptive statistics of *PIN*

The Probability of Informed trading (PIN) is estimated at quarterly frequency from 1983 to 2004 using the entire three months trade and quote data from TAQ. A breakdown of our stock *PIN* sample over time is provided in Panel A. The correlations among PIN and other stock characteristics are reported in Panel B.

Panel A: Summary Statistics on PIN

Year	# of stocks per quarter	% of NYSE/AMEX stocks	% of NASNAQ stocks	mean	std dev
1983	1915	100%	0.0%	22.5%	10.2%
1984	1747	100%	0.0%	25.2%	13.0%
1985	1812	100%	0.0%	24.1%	11.8%
1986	1828	100%	0.0%	23.4%	11.1%
1987	3732	46.7%	53.3%	27.0%	12.1%
1988	3399	50.0%	50.0%	28.1%	13.4%
1989	3373	49.7%	50.3%	27.4%	13.3%
1990	3321	49.4%	50.6%	27.7%	13.6%
1991	3362	50.4%	49.6%	26.7%	12.7%
1992	4117	43.4%	56.6%	27.2%	13.0%
1993	4106	53.8%	46.2%	25.4%	12.0%
1994	5258	36.3%	63.7%	27.4%	12.9%
1995	5500	35.1%	64.9%	27.2%	12.5%
1996	6028	33.7%	66.3%	26.6%	12.1%
1997	6473	32.5%	67.5%	25.8%	11.8%
1998	6453	32.6%	67.4%	25.6%	11.8%
1999	5879	33.9%	66.1%	26.0%	12.1%
2000	5526	33.1%	66.9%	26.3%	12.6%
2001	4842	32.3%	67.7%	28.0%	13.6%
2002	4476	36.4%	63.6%	25.3%	11.6%
2003	3999	39.4%	60.6%	22.7%	9.8%
2004	3727	42.0%	58.0%	21.1%	9.5%
All	4130	51.3%	48.7%	25.8%	12.1%

Panel B: Cross-correlation

	PIN	log(Size)	log(BM)	Mom
log(Size)	-0.536			
log(BM)	0.169	-0.193		
Mom	-0.066	0.058	-0.148	
Amihud	0.557	-0.872	0.190	-0.198

Table 6: CS measure decomposition across *Trade_PIN* sorted fund deciles

In each quarter and for each fund, we compute a *trade_PIN* variable by value-weighing PIN of stocks traded by the fund during the quarter using the dollar value of the trade. At the end of each quarter from 1983 to 2004, we sort all mutual funds in our sample into deciles according to their *trade_PIN*s and decompose the CS measure within each decile. The last column reports the average 4-factor (Fama-French three factors and the momentum factor) risk adjusted mutual fund returns. *t*-values associated with the average measures are reported in *italic*s. The CS measure and its components are winsorized at 1st and 99th percentiles to alleviate the effect of outliers.

Trade_PIN	Total CS (=1+2+3)	Passive CS^P (1)	Adj CS^{adj} (2)	Active CS^A (3=3a+3b)	Info trading CS^{inf} (3a)	Liquidity Prov CS^{liq} (3b)	4f-adj MF return
All stocks	23.5	13.9	-1.8	14.2	3.6	8.8	-23.6
	1.91	*1.19*	*-2.38*	*2.09*	*0.55*	*1.50*	*-2.55*
Low	-2.9	-7.6	-0.4	3.4	-12.1	16.2	-42.2
	-0.29	*-0.70*	*-0.20*	*0.42*	*-2.02*	*2.57*	*-3.97*
2	11.4	10.4	-0.7	2.6	-6.4	8.9	-35.7
	0.92	*0.87*	*-0.47*	*0.40*	*-0.93*	*1.28*	*-3.85*
3	11.8	9.2	-1.0	5.5	-5.5	9.8	-28.6
	1.04	*0.81*	*-0.69*	*0.88*	*-0.78*	*1.65*	*-2.59*
4	10.3	8.3	-1.1	5.8	-3.5	6.0	-33.8
	1.01	*0.76*	*-0.81*	*0.76*	*-0.54*	*0.89*	*-3.52*
5	28.6	23.3	-2.3	6.4	2.5	5.5	-15.5
	2.17	*1.80*	*-1.52*	*0.72*	*0.31*	*0.74*	*-1.36*
6	31.9	19.2	-2.4	18.7	5.6	9.4	-22.3
	2.07	*1.20*	*-1.52*	*1.69*	*0.62*	*1.10*	*-1.65*
7	28.4	19.4	-0.9	17.2	9.7	0.2	-28.1
	1.52	*1.17*	*-0.56*	*1.18*	*0.89*	*0.03*	*-1.93*
8	30.9	14.6	-3.4	25.0	8.6	13.7	-20.5
	1.73	*0.87*	*-2.05*	*2.26*	*0.84*	*1.64*	*-1.22*
9	35.1	15.7	-2.7	26.6	16.8	7.6	-17.4
	1.75	*0.82*	*-1.35*	*2.38*	*1.70*	*0.77*	*-1.06*
High	50.0	26.5	-3.2	31.2	20.4	10.4	8.3
	2.70	*1.43*	*-1.40*	*2.83*	*2.25*	*1.37*	*0.65*
High - Low	52.9	34.1	-2.8	27.8	32.5	-5.8	50.5
	2.87	*1.94*	*-0.93*	*2.26*	*3.50*	*-0.68*	*3.27*

Table 7: CS measure decomposition across *trade_rel_OIB* sorted fund deciles

In each quarter and for each fund, we compute a *trade_rel_OIB* variable by value-weighing *rel_OIB* of stocks traded by the fund during the quarter using the dollar value of the trade. At the end of each quarter from 1983 to 2004, we sort all mutual funds in our sample into deciles according to their *trade_rel_OIB*s and decompose the CS measure within each decile. *t*-values associated with the average measures are reported in *italic*s. The CS measure and its components are winsorized at 1st and 99th percentiles to alleviate the effect of outliers.

Trade_rel_OIB	Total CS (=1+2+3)	Passive CS^P (1)	Adj CS^{adj} (2)	Active CS^A (3=3a+3b)	Info trading CS^{inf} (3a)	Liquidity Prov CS^{liq} (3b)
Low	1.9	-7.9	-2.0	14.9	-11.8	23.2
	0.12	*-0.59*	*-1.12*	*1.15*	*-1.09*	*2.62*
2	7.7	3.2	-0.4	6.3	-7.4	12.5
	0.59	*0.29*	*-0.30*	*0.64*	*-0.81*	*1.73*
3	7.1	5.9	-1.3	7.2	-5.2	8.7
	0.56	*0.48*	*-0.88*	*0.99*	*-0.69*	*1.29*
4	10.4	6.0	-2.4	9.6	-4.0	12.0
	0.86	*0.49*	*-1.57*	*0.91*	*-0.47*	*1.57*
5	30.2	23.1	0.5	7.9	-0.3	7.2
	2.24	*1.71*	*0.31*	*0.88*	*-0.04*	*0.99*
6	30.1	16.4	-2.6	17.1	12.2	3.1
	1.90	*1.06*	*-1.50*	*2.23*	*1.37*	*0.39*
7	31.9	22.9	-2.3	13.3	7.0	4.9
	1.96	*1.37*	*-1.47*	*1.29*	*0.76*	*0.56*
8	40.8	19.7	-2.6	26.3	16.7	7.8
	2.32	*1.21*	*-1.75*	*2.40*	*1.73*	*0.84*
9	37.8	20.8	-6.0	29.0	20.4	7.1
	1.87	*1.10*	*-2.62*	*2.97*	*1.95*	*0.78*
High	55.1	23.7	-1.8	34.4	26.9	6.3
	2.89	*1.21*	*-0.71*	*3.69*	*3.26*	*0.82*
High - Low	53.2	31.6	0.2	19.5	38.7	-16.9
	2.00	*1.25*	*0.08*	*1.22*	*2.83*	*-1.35*

Table 8: CS measure decomposition across *trade_theta* sorted fund deciles

In each quarter and for each fund, we compute a *trade_theta* variable by value-weighing the information asymmetry component of the bid-ask spread (*theta*) of stocks traded by the fund during the quarter using the dollar value of the trade. *Theta* is computed for each stock during each quarter using the procedures in Madhavan, et al. (1997. At the end of each quarter from 1983 to 2004, we sort all mutual funds in our sample into deciles according to their *trade_theta*s and decompose the CS measure within each decile. *t*-values associated with the average measures are reported in *italic*s. The CS measure and its components are winsorized at 1st and 99th percentiles to alleviate the effect of outliers.

Trade_theta	Total CS (=1+2+3)	Passive CS^P (1)	Adj CS^{adj} (2)	Active CS^A (3=3a+3b)	Info trading CS^{inf} (3a)	Liquidity Prov CS^{liq} (3b)
Low	10.4	7.0	-2.0	7.5	-9.3	16.2
	0.79	*0.49*	*-1.33*	*0.96*	*-1.36*	*2.38*
2	13.6	6.0	-1.8	8.6	-5.4	14.1
	1.18	*0.50*	*-1.12*	*1.26*	*-0.75*	*1.92*
3	10.8	5.7	-1.0	6.7	-3.6	9.8
	0.92	*0.43*	*-0.62*	*0.96*	*-0.49*	*1.29*
4	8.0	4.4	-3.7	6.7	-5.6	13.9
	0.71	*0.35*	*-2.07*	*0.84*	*-0.75*	*1.72*
5	21.5	21.8	-2.1	3.6	-5.7	8.4
	1.54	*1.57*	*-1.07*	*0.51*	*-0.70*	*1.06*
6	23.1	17.0	-2.8	10.2	6.8	1.1
	1.42	*1.12*	*-1.17*	*0.95*	*0.69*	*0.12*
7	27.8	13.8	-3.3	24.7	19.8	-2.1
	1.63	*0.89*	*-1.88*	*1.73*	*1.93*	*-0.23*
8	43.5	22.4	-2.1	27.4	15.2	9.2
	2.50	*1.45*	*-1.04*	*2.48*	*1.61*	*1.17*
9	39.2	17.4	-2.8	29.5	21.6	6.9
	1.90	*0.88*	*-1.30*	*2.54*	*2.02*	*0.70*
High	56.3	30.0	-3.5	32.4	23.7	7.3
	2.74	*1.47*	*-1.26*	*2.74*	*2.28*	*0.84*
High - Low	42.0	20.6	-1.5	23.1	31.7	-8.9
	2.17	*0.99*	*-0.44*	*1.66*	*3.00*	*-0.94*

Table 9: Fund-level characteristics

Panel A reports the average fund-level characteristics across the *trade_PIN* sorted deciles. Fund-level stock characteristics are computed by value-weighing the stock characteristics of stocks held by the fund at quarter end using the dollar value of the holding. All characteristics are winsorized at 1st and 99th percentile to alleviate the effect of outliers. The correlations among the characteristics are reported in Panel B.

Panel A: Average fund-level characteristics across *trade_PIN* sorted fund deciles

Trade _PIN	num _stock	trade _PIN	fund _holding	fund _size	fund _bm	fund _mom	fund _amihud	age	turnover	expense	TNA	pct _flow	% of AGG	% of Growth	% of GNI
Low	64	11.2%	0.25%	32.9	0.56	0.232	4.5%	53.3%	0.680	1.14%	1020.9	2.74%	3.7%	50.9%	45.4%
2	72	12.3%	0.26%	30.1	0.56	0.253	5.1%	55.3%	0.772	1.12%	972.5	2.11%	4.5%	54.1%	41.5%
3	74	13.0%	0.27%	28.0	0.56	0.268	5.5%	55.9%	0.841	1.13%	848.4	1.98%	5.6%	54.9%	39.5%
4	74	13.7%	0.28%	25.4	0.55	0.282	6.3%	54.2%	0.855	1.16%	740.8	1.95%	7.9%	60.4%	31.7%
5	75	14.4%	0.32%	20.5	0.55	0.304	7.4%	53.8%	0.880	1.20%	719.1	1.82%	11.3%	61.5%	27.2%
6	75	15.3%	0.37%	15.6	0.55	0.329	8.8%	50.8%	0.909	1.22%	636.8	2.42%	17.2%	59.7%	23.1%
7	74	16.3%	0.44%	11.2	0.54	0.365	10.9%	48.1%	0.945	1.26%	557.5	3.23%	24.0%	59.8%	16.1%
8	73	17.7%	0.54%	6.6	0.55	0.381	14.3%	45.3%	0.970	1.30%	404.4	2.85%	28.6%	59.6%	11.9%
9	81	19.4%	0.63%	3.9	0.54	0.393	18.9%	42.6%	0.904	1.32%	353.9	3.92%	30.0%	61.8%	8.2%
High	97	22.7%	0.91%	2.1	0.62	0.339	28.4%	37.6%	0.725	1.34%	295.1	5.29%	29.2%	64.9%	5.9%
H-L	33	11.5%	0.66%	-30.8	0.06	0.107	24.0%	-15.7%	0.044	0.20%	-725.8	2.54%	25.5%	14.1%	-39.5%
t-value	11.5	73.2	53.5	-9.8	3.0	6.2	47.4	-14.5	1.6	12.9	-14.9	4.6	13.7	7.5	-26.8

Panel B: Correlations among fund-level characteristics

	trade_PIN	fund _holding	fund_size	fund_bm	fund_mom	fund _amihud	age	turnover	expense	TNA
fund_holding	0.336									
fund_size	-0.612	-0.285								
fund_bm	0.336	0.177	-0.461							
fund_mom	0.087	0.016	-0.095	-0.308						
fund_amihud	0.731	0.417	-0.516	0.311	0.013					
age	-0.142	0.100	0.084	-0.051	-0.041	-0.168				
turnover	0.018	-0.130	-0.089	-0.074	0.210	-0.009	-0.105			
expense	0.008	-0.146	0.037	-0.181	0.061	0.132	-0.256	0.220		
TNA	-0.209	0.392	0.155	-0.069	-0.015	-0.173	0.231	-0.127	-0.175	
pct_flow	0.082	0.004	-0.086	0.037	0.110	0.045	-0.135	0.010	0.035	-0.009

Table 10: Average past one-year return of stocks Bought / Sold / Held by mutual funds across *trade_PIN* sorted deciles

At the end of each quarter from 1983 to 2004, we sort all mutual funds in our sample into deciles according to their *trade_PIN*s. For each fund, we then compute the value-weighted average past one-year return of stocks in the "Buy" portfolio (stocks recently bought by the fund), the "Sell" portfolio (stocks recently sold by the fund) and the "Hold" portfolio (stocks held by the fund throughout the quarter). These past returns are then averaged across funds and across time. *t*-values associated with the average measures are reported in *italic*s.

trade_pin	Past One-year Return				
	Buy	Sell	Hold	Buy-sell	t-value
Low	20.9%	24.3%	22.2%	-3.4%	*-5.74*
2	23.2%	26.4%	24.6%	-3.2%	*-5.18*
3	25.1%	26.8%	25.6%	-1.7%	*-2.96*
4	26.7%	29.6%	27.2%	-2.9%	*-4.08*
5	28.5%	32.1%	29.2%	-3.6%	*-4.48*
6	32.1%	36.2%	32.4%	-4.1%	*-3.66*
7	36.2%	39.6%	35.2%	-3.4%	*-3.13*
8	39.2%	43.8%	37.5%	-4.6%	*-3.60*
9	40.2%	46.1%	37.8%	-5.9%	*-4.65*
High	34.3%	46.6%	34.0%	-12.3%	*-8.93*
H-L	13.47%	22.36%	11.73%		
	6.37	*8.42*	*6.47*		

Table 11: Cross-sectional regressions

We regress the next quarter components of CS measure on several fund-level characteristics during each quarter from 1983 to 2004. Variables are winsorized at 1st and 99th percentiles to alleviate the effect of outliers. All explanatory variables (except for the style dummy variables) are cross-sectionally demeaned and standardized so the corresponding coefficients can be interpreted as the impact on return of one standard deviation change in the variable. Finally, the regression coefficients are averaged across time and the associated t-values are computed using Newey-West formula of lead / lag of 8 to account for the autocorrelations in the error terms. *t*-values associated with the average measures are reported in *italic*s. *trade_pin* is the (log) average PIN of stocks recently traded by the funds; *log_fund_size* is the (log) average market cap of stocks held by the fund; *log_fund_bm* is the (log) average book-to-market ratio of stocks held by the fund; *fund_mom* is the average past one-year returns on stocks held by the fund; *fund_amihud* is the average Amihud illiquidity measure, in terms of percentile rank in the cross-section, of stocks held by the fund; *log_TNA* is the (log) total net assets under management by the fund; *Age* is the age of the fund since inception, in terms of percentile rank in the cross-section; *expense* is the expense ratio of fund; *turnover* is the turnover rate of the fund; *dummy_growth* is a dummy variable which assumes 1 if the self-reported investment objective is “growth” and 0 otherwise; *dummy_Agg* is a dummy variable which assumes 1 if the self-reported investment objective is “AGG” and 0 otherwise.

	Intercept	trade_pin	log_fund_size	log_fund_bm	fund_mom	fund_amihud	log_TNA	Age	expenses	turnover	dummy_growth	dummy_Agg	Average R^2
							LHS = CS						
coeff	0.0018	0.0020	0.0014	0.0006	0.0016	-0.0002	0.0000	-0.0001	-0.0004	0.0003	0.0006	0.0036	0.20
t-value	*1.25*	*2.79*	*1.42*	*0.52*	*1.69*	*-0.22*	*0.12*	*-0.64*	*-0.95*	*0.60*	*0.67*	*3.05*	
							LHS = CS^{inf}						
coeff	0.0001	0.0010	0.0008	0.0008	0.0011	0.0001	0.0000	-0.0003	-0.0004	0.0001	-0.0001	0.0015	0.12
t-value	*0.20*	*3.13*	*1.41*	*1.42*	*1.54*	*0.23*	*-0.21*	*-1.58*	*-1.57*	*0.26*	*-0.20*	*2.64*	
							LHS = CS^{liq}						
coeff	0.0013	-0.0003	0.0000	-0.0005	-0.0002	0.0004	0.0000	-0.0004	0.0001	0.0004	-0.0005	-0.0011	0.09
t-value	*2.56*	*-0.98*	*-0.07*	*-1.51*	*-0.56*	*1.09*	*0.03*	*-2.94*	*0.55*	*1.60*	*-1.37*	*-1.54*	

Table 12: Persistence of the informed trading component and the liquidity provision component of the mutual fund CS measure

At the end of each quarter from 1983 to 2004, we sort funds into deciles based on their CS measure during the quarter. We then tabulate the average CS measure across the deciles during the next quarter. We repeat the sorting exercise also for the components of the CS measure: CS^{P}, CS^{inf} and CS^{liq}. *t*-values associated with the average measures are reported in *italic*s.

	Total CS		Passive CS^{P}		Info trading Cs^{inf}		Liquidity Prov Cs^{liq}	
	Qtr t	Qtr t+1	Qtr t	Qtr t+1	Qtr t	Qtr t+1	Qtr t	Qtr t+1
Low	-6.51%	-0.08%	-6.79%	-0.02%	-4.49%	-0.09%	-4.60%	0.14%
	-28.15	*-0.39*	*-28.30*	*-0.10*	*-23.01*	*-0.71*	*-18.89*	*0.86*
2	-3.20%	0.17%	-3.26%	0.05%	-1.99%	0.03%	-1.85%	0.03%
	-22.54	*1.08*	*-22.35*	*0.37*	*-20.14*	*0.30*	*-16.23*	*0.34*
3	-1.90%	0.13%	-1.95%	0.09%	-1.16%	0.01%	-1.01%	0.04%
	-16.66	*0.99*	*-16.19*	*0.74*	*-16.70*	*0.11*	*-13.35*	*0.50*
4	-0.97%	0.13%	-1.05%	0.09%	-0.62%	0.04%	-0.50%	0.08%
	-9.38	*0.90*	*-9.39*	*0.62*	*-12.02*	*0.46*	*-9.18*	*1.29*
5	-0.21%	0.31%	-0.30%	0.26%	-0.22%	0.03%	-0.11%	0.07%
	-1.96	*1.91*	*-2.68*	*1.85*	*-4.73*	*0.34*	*-2.41*	*1.08*
6	0.51%	0.27%	0.43%	0.04%	0.17%	0.07%	0.26%	0.08%
	4.31	*1.71*	*3.70*	*0.30*	*3.46*	*0.79*	*5.93*	*1.33*
7	1.31%	0.27%	1.22%	0.17%	0.60%	0.12%	0.66%	0.12%
	9.34	*1.71*	*9.10*	*1.05*	*9.10*	*1.14*	*12.75*	*1.64*
8	2.27%	0.32%	2.17%	0.18%	1.16%	0.06%	1.20%	0.15%
	12.38	*1.61*	*13.50*	*1.00*	*11.65*	*0.69*	*17.24*	*2.09*
9	3.69%	0.41%	3.54%	0.32%	2.10%	0.08%	2.03%	0.00%
	13.25	*1.76*	*17.11*	*1.50*	*12.12*	*0.63*	*20.79*	*-0.02*
High	7.70%	0.65%	7.42%	0.15%	5.05%	0.29%	4.70%	0.16%
	15.40	*1.84*	*20.13*	*0.47*	*12.79*	*1.75*	*23.62*	*1.30*
High - Low	14.21%	0.73%	14.21%	0.17%	9.54%	0.38%	9.31%	0.02%
	22.87	*1.83*	*27.51*	*0.44*	*18.86*	*2.80*	*23.89*	*0.13*