Opinion Divergence Among Professional Investment Managers

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Opinion Divergence Among Professional Investment Managers

Abstract

We find that opinion divergence among professional investment managers is commonplace, using a large sample of proprietary transaction-level institutional trading data. When managers trade together, future returns are similar regardless if they are all buying or selling, inconsistent with the notion that professional investment managers possess stock picking ability or private information that is of investment value. However, when managers trade against each other, subsequent returns are low, especially for stocks that are difficult to short. This U-shaped disagreement-return relationship is consistent with Miller's (1977) hypothesis that, in the presence of short-sale constraints, opinion divergence can cause an upward bias in prices.

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1. Introduction

In this paper we examine the daily trading activity of a large sample of professional investment managers. Using a unique dataset, which contains the daily trades of 1,730 different funds from 30 different fund families, we examine the tendency for managers to trade with and against one another. We conduct our analysis both across and within fund families. We are able to observe instances when the managers in our sample are in total agreement, as well as instances when the number of managers that are buying a stock is equal to the number of managers that are selling a stock. We document that manager disagreement, even among managers working at the same fund company, is commonplace.

We use our findings to test two important hypotheses. First, we test whether the fund managers in our sample possess private information. There are two sets of theories regarding how aggregated fund trading should be related to private information and abnormal returns. Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994) claim that when numerous funds trade in the same direction it may be due to their sharing similar private information. These papers imply that we might expect to see abnormal returns that are in the same direction that the crowd is trading.

Scharfstein and Stein (1990) observe that it is costly for a manger to trade against the crowd, for if she is wrong she looks bad relative to her peers and may be punished. Therefore, even if managers do have private information they may choose to ignore it, for the cost will be very high if the information turns out to be wrong. This theory implies that when managers do trade against the crowd they ought to have extremely good information, as going against the crowd is a risky thing to do. Therefore, we might expect abnormal returns to be in the opposite direction of the crowd, so long as there are some dissenters.

In our data, we can observe the number of funds in our sample that bought and sold a given stock on a particular day. For example, we might see that 100 funds bought Microsoft on a particular day, while 10 funds sold it on that same day. The argument of Scharfstein and Stein implies that the subsequent return of Microsoft ought to be low, as the 10 managers that sold Microsoft would not trade against the crowd unless they had very good information. If the alternative theory is correct, the subsequent return of Microsoft ought to be high, as the 100 managers that bought Microsoft may be sharing information that the other 10 managers do not have access to. If none of the managers possess private information, then an imbalance in the ratio of buyers to sellers should not predict stock returns.

We also examine whether opinion divergence among the fund managers in our sample can predict stock returns. We use divergence in the daily trading among the funds in our sample as a proxy for opinion divergence. The hypothesis, first put forth by Miller (1977), contends that when short selling is constrained prices will reflect the more optimistic valuations. Miller contends that optimists will buy the stock, but pessimists will not short the stock due to short sale constraints.[1] Therefore, large opinion divergences will result in large upward biases in share prices and subsequent low returns.[2] This result should especially hold for stocks that are difficult or costly to short.

One important aspect that makes our study unique is that we observe *daily trades*. Kothari and Warner (2001) find that performance measures, which use fund *portfolios*, have little ability to detect abnormal performance. Kothari and Warner further find that analyzing fund *trades* can substantially improve test power. To our knowledge, we are the first paper that uses trades to detect abnormal performance. Chen, Jegadeesh, and Wermers (2000) use changes in quarterly and/or semiannual fund holdings as a *trade*

[1]Harrison and Kreps (1978), Diamond and Verrecchia (1987), Morris (1996), Chen, Hong, and Stein (2002), Duffie, Garleanu, and Pedersen (2002), and Viswanathan (2002) also have models in which the investor with the optimistic valuation holds the shares.

[2]Pontiff (1996) and Jones and Lamont (2003) provide examples of how short sale constraints can limit arbitrage and mispricings can persist. Shleifer and Vishny (1997) show this in a theoretical setting.

proxy to measure aggregate fund performance.[3] Wermers (1999) looks at a trade proxy to determine whether funds "herd" when they trade.

Both Wermers and Chen et al. use CDA data, which consists of either quarterly or semiannual stockholdings data of US mutual funds (see Wermers or Chen et al.). The CDA data reports either semiannual or quarterly fund holdings, which are clearly different than trades. Two issues can arise with holdings data that do not arise in our trade data. First, if a fund trades at the beginning of quarter and the abnormal performance is short lived (e.g. less than 3 months) then it will not be measured. Second, a fund may trade more than once in the same stock within a quarter, but the CDA data only allows the user to see quarter beginning and quarter end holdings, or aggregated trades throughout the quarter. To see why this matters, consider a manager who sells his entire holdings of 100 shares at the beginning of the quarter, then later change his mind and buys 90 shares of the same stock at the end of the quarter. In the CDA data it will appear that the manager had a negative view of the stock, as he decreased his holdings by 10 shares, but at quarter end the manager was actually buying the stock.

Ours is also the first study to use trades as a proxy for opinion divergence. Diether, Malloy, and Scherbina (2002) and Boehme, Danielsen, and Sorescu (2005) use dispersion in analysts' forecasts as a proxy for opinion divergence. They find that when forecast dispersion is high returns are low, and conclude that this result is driven by opinion divergence and short sale constraints.[4] Clearly a fund manager's private trade is a much different opinion proxy than is an analyst's public forecast. Furthermore, we show that opinion divergence among fund managers occurs in different types of stocks than it does with analysts.

[3]Gibson, Saffiedine, and Sonti (2004) find that institutions make profitable investments in companies that are having SEO's. Baker, Litav, Wachtell, and Wurgler (2004) find that managers can pick stocks around earnings announcements.

[4] Recent papers by Ghysels and Juergens (2001), Cao, Wang, and Zhang (2003), Liu, Xu, and Yao (2003), Johnson (2004), and Qu, Starks, and Yan (2004) contend that the relationship between analyst forecast dispersion and future returns can be explained by factors other than opinion divergences and optimistic valuations.

Chen, Hong, and Stein (2002) build a model in which opinion divergence and reductions in breadth (the number of funds that own a stock) create short sale constraints and an upward bias in prices. Chen et al. then show empirically, using CDA data, that when breadth is reduced subsequent returns are low. Chen et al. attribute their results to the fact that most likely there are funds or other parties that do not own the stock, would like to sell the stock, but do not due to short sale constraints. This is a reasonable argument, although Chen et al.'s empirical measure only captures short sale constraints, it does not measure opinion divergence.[5] In a recent study, Alexandridis, Antoniou, and Petmezas (2007) find that UK acquirers subject to high opinion divergence earn lower future returns.

Our results can be summarized as follows. First, we find that disagreement among managers is commonplace; this is true both across fund families and within fund families where managers are presumable sharing the same information. We measure disagreement using a simple buy proportion. For example, if 50 funds buy Microsoft on a given day, and fifty funds sell Microsoft on that same day, then Microsoft's buy proportion is buys/(buys + sells) = 50/100 = 0.5 on that day. We find that 37% of our stock-day observations have an across family buy proportion that is between 0.3 and 0.7, which we interpret as an opinion divergence band.

Our results imply that disagreement among fund managers arises in different types of stocks than does disagreement among analysts. We find that opinion divergence among fund managers is more common among large, low book-to-market stocks with relatively low past returns. This is true both within and across fund families. Diether, Malloy, and Scherbina (2002) report that dispersion in analyst's forecasts is higher for small, high book-to-market stocks with low past returns. This is not surprising given that analyst "agreement" is typically measured by accuracy of earnings per share estimates whereas manager

[5] Nagel (2005) finds that Chen et al.'s results reverse out of sample.

"agreement" is measured here by decisions that involve valuation. To the extent that earnings per share plays a smaller role in valuation there will be inconsistencies between the two sets of results.

When the managers in our sample trade together the stocks tend to be small, have high book-to-market ratios and past returns that are in the same direction that the crowd is trading (crowd sells past losers, buys past winners). These results are consistent with the findings in Wermers (1999), who finds, using CDA data, that funds tend to herd in stocks with these same characteristics.

We find no evidence of manager stock picking ability. Stocks that are highly bought have roughly the same future returns, as do stocks that are highly sold. Even instances in which all of the managers in our sample that are trading in the same stock on same day trade in the same direction the future returns are generally the same regardless if the managers are buying or selling.[6] These results are consistent both across and within fund families and imply that managers do not have private information, but may trade together due to reputation concerns.[7]

We do find that returns begin to decrease as disagreement among fund managers increases, and this result holds even after controlling for size, book-to-market and momentum affects. This result is consistent when disagreement is measured across and within fund families. Importantly, this result is stronger for stocks that are more costly to short. This finding is consistent with the hypothesis that opinion divergence coupled with short sale constraints will cause an upward bias in share prices. When plotted, the

[6] Gibson, Saffiedine, and Sonti (2004) find that institutions make profitable investments in companies that are having SEO's, but show no such ability with non-SEO stocks. Jensen (1968), Gruber (1996), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997), and Ferson and Khang (2002) also imply that fund managers do not possess extraordinary investment abilities.

[7] Chen, Jegadeesh and Wermers (2000) measure broad based fund manager ability using trades (or a trade proxy) and they find that managers do possess ability, as stocks that are highly bought outperform stocks that are highly sold. However, Duan, Hu, and McLean (2005) find that Chen, Jegadeesh, and Wermers (2000)'s results become much weaker or nonexistent out of sample (post 1995), and in this paper we examine trades that occurred in 2001.

disagreement-return relationship displays a U-shaped pattern. These findings are consistent with Ali and Trombley (2006), who find that momentum returns are positively related to short sale constraints.[8]

The rest of this paper is organized as follows. Section 2 describes our data. Sections 3 and 4 are our univariate and regression results, respectively. In section 5 we examine intra-family opinion divergence. Section 6 concludes the paper.

2. Data Description

We obtained transaction-level institutional trading data from the Abel/Noser Corporation, a leading execution quality measurement service provider for institutional investors.[9] Abel/Noser data include transactions from two types of institutional investors: Investment Managers and Plan Sponsors. Investment Managers are fund families such as Fidelity Investments. An example of a Plan Sponsor is United Airlines Pension Plan.[10] We only include Investment Managers in our sample because Plan Sponsors are not usually involved in investment decisions and typically sub-contract this function out to investment managers. We also eliminated transactions that consisted of less than 100 shares.

The Abel/Noser data we use are similar in nature to the Plexus data used by several previous studies on institutional trading costs (e.g., Keim and Madhavan (1995, 1997)). Goldstein, Irvine, Kandel, and Wiener (2004) also used the Abel/Noser data to study brokerage commissions. For each transaction, the data include the date of the transaction, the stock traded (identified by both symbols and CUSIPs), the number of shares traded, the dollar principal traded, commissions paid by the fund, and whether it is a buy or sell by the fund. The data were provided to us under the condition that the names of all funds and

[8] See also Thomas (2006) for a discussion, and Ali, Hwang, and Trombley (2003) for related findings on the book-to-market anomaly.

[9] We thank the Abel/Noser Corporation for generously providing us with the institutional trading data.

[10] Fidelity Investments and United Airlines Pension Plan are used for the purpose of illustration only. The Abel/Noser data are anonymous, and we do not know the identities of the institutions in our sample.

fund families would be removed from the data. However, identification codes were provided enabling us to separately identify them.

Our sample period is from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, volume and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We also obtain institutional holdings data from Thomson Financial CDA/Spectrum Institutional Holdings (13f) database.

3. Portfolio Analyses

In this section we assign stocks to portfolios based on certain characteristics, and then draw conclusions about the differences in average returns or characteristics among the portfolios. For each of the trading days in our sample we take each stock that had at least five fund managers trading in it *on that day* and calculate a buy proportion measure.[11] Our buy proportion measure is the number of managers that buy stock i on day t divided the total number of transactions (buys and sells) for stock i on day t.[12] Once the buy proportion measure is calculated we place each stock into one of five opinion portfolios. If the buy proportion measure is equal to 1, we place the stock in the *AllBuy* portfolio. If the buy proportion measure is equal to 0, we place the stock in the *AllSell* portfolio. If our buy proportion measure is less than 1 but greater than 0.7, we place the stock in the *MinSell* (Minority Selling) portfolio. If our buy proportion measure is less than 0.3 but greater than 0, we place the stock in the *MinBuy* (Minority Buying) portfolio. Finally, if our buy proportion measure is less than 0.7 but greater than 0.3, we place

[11] We chose five managers because this is often the minimal number of managers used in the herding literature (see, e.g., Lakonishok, Shleifer, and Vishny (1992) and Sias (2004)). In addition, the results and conclusions do not change when we use a sample that consists of at least three managers trading on a given day.

[12] The results of our analysis are similar when dollar value of trades is used to measure trading activity.

the stock in the *Disagree* portfolio.[13] All of the returns are buy and hold market-adjusted (the return of the value weighted CRSP index is subtracted from each stock's return) returns of equal-weighted portfolios.

3.1. Portfolio Characteristics

Table 1 displays the frequency and average characteristics of the stocks in each of the different opinion portfolios. The first two columns in table 1 display the number and percentage of stock-day observations that fall into each of the different opinion portfolios. 37.7% of the observations fall into the *Disagree* portfolio; this is the most common portfolio for our observations to be in. It is more common for the managers in our sample to buy in unison than it is for them to sell in unison. The *MinSell* and *AllBuy* portfolios make up 27.3% and 14.2% of the sample, while the *MinBuy* and *AllSell* portfolio*s* make up only 14.9% and 5.8% of the sample.

The next 3 columns in table 1 explore the characteristics of the stocks in the different portfolios. The stocks in the *Disagree* portfolio have, on average, the largest market values (average is $26,498 million), the lowest book-to-market ratios (average is 0.39) and the lowest past returns (average is –4.25%) of the 5 opinion portfolios. Diether, Malloy and Scherbina (2002) report that dispersion in analyst's forecasts is higher for small, high book-to-market stocks with low past returns. It seems that fund manager and analyst opinion divergence occurs among different stocks, as the only commonality is low past returns.

Table 1 also reveals that the stocks in the four portfolios in which the managers are trading together tend to be smaller, with higher book-to-market ratios. The *AllBuy* portfolio has very high past returns, and implies momentum trading. These findings are consistent with Wermers (1999) who finds that herding is

[13] In later regression analysis we use a continuous measure for opinion divergence. In addition, we perform the univariate analysis using alternative ranges to define our *Disagree* portfolio. The results are similar.

more prevalent among growth funds and in small stocks. Wermers also finds evidence of institutional momentum trading.

3.2. Portfolio Returns Over Different Horizons

In table 2 we calculate future returns for 1,6, and 12-month holding periods. To calculate our portfolio returns, we form portfolios on each day, and calculate the future returns of that portfolio. We do that for each of the trading days in our sample, and the returns displayed in the subsequent tables are simply the average returns of the different daily portfolios. The returns are market-adjusted ($r_{it} - r_{vw}$), as we subtract the value-weighted return of the market from the return of each stock before the portfolios are made. The holding periods do overlap, so we calculate the *p-values* using the method of Newey and West (1987), setting the lags equal to the number of statistically significant lags that we observe in the data.

In this section we conduct tests to see whether or not the managers in our sample possess private information. As mentioned in the introduction, the results in Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994) imply that if managers possess information, then we should expect to see abnormal returns that are in the same direction that the crowd is trading. Table 2 shows that *AllSell* portfolios beat the *AllBuy* portfolios at the 6 and 12-month horizons by 51% (p-value = 0.346) and 4.36% (p-value = 0.005). At the 1-month horizon the *AllBuy* portfolio beat the *AllSell* portfolio by only 0.31% (p-value = 0.638). These results imply that the managers in our sample do not possess private information and in fact would have done better had they not traded at all.

Scharfstein and Stein (1990) argue that when managers do trade against the crowd they ought to have extremely good information, as going against the crowd is a risky thing to do. Therefore, we might expect abnormal returns to be in the opposite direction of the crowd, so long as there are some dissenters. If the dissenting managers in our sample had private information, then the *MinBuy* portfolio should have the highest returns and the *MinSell* portfolio should have the lowest returns. In the *Minbuy* portfolio the buyers are in the minority, but the returns of this portfolio are low relative to the others, so it does not seem that the buyers here possess any private information. In the *Minsell* portfolio, the sellers are in the minority. The returns of this portfolio are relatively low, however the returns are similar to those of the *MinBuy* portfolio and are larger than those of the *Disagree* portfolio. This pattern does not support the notion that the private managers in our sample have private information.

Table 2 shows that the *Disagree* portfolio has the lowest returns at every horizon. The difference between the *Disagree* portfolio's returns and the *AllBuy* portfolio's returns are 2.85%, 9.03% and 6.08% over 1, 6, and 12-month horizons. All of the differences are significant at the 99% level. The difference between the *Disagree* portfolio's returns and the *AllSell* portfolio's returns are 2.54%, 9.54% and -10.44% over 1, 6, and 12-month horizons. All of the differences are significant at the 99% level. Table 2 also shows that the *MinBuy* and *MinSell* portfolios have lower returns than do the *AllBuy* and *AllSell* portfolios at every horizon. This pattern implies that as divergence in opinion increase returns begin to decrease, consistent with the hypotheses that opinion divergence coupled with short sale constraints will cause an upward bias in share prices and subsequent low returns. We plot these results in figure 1, which displays a U-shaped pattern. Given that our results are robust and similar at 1, 6 and 12-month horizons, we will only measure 6-month returns throughout the rest of the paper.

3.3. Sorting on Size and Buy Proportion

Table 3 performs a two-way sort on firm size and divergence and tests whether our results in table 2 simply captured a size affect. To create the size portfolios we sort of all of the stocks, which traded five or more times on at least one day, on their market values. We then placed our stocks in one of five size quintiles based on their size ranking. The market values we use are the market values observed the first time a stock enters one of our daily samples, which is the first day that a stock trades more than five times. The average size of the stocks each portfolio and the number of trades within each portfolio are also displayed. The averages reveal that there is a good deal of variation in the market values within our sample. The stocks that in the largest quintile have an average market value of $37.05 billion, while the stocks in the smallest quintile have an average market value of $331 million.

Table 3 reveals that the pattern in table 1 is consistent across all five of the size quintiles. The *Disagree* portfolios returns are lower than are those of both the *AllBuy* and the *AllSell* portfolios in each of the five size quintiles. Table 3 also implies that opinion divergence has its strongest affect on small stocks. The differences between the *Disagree* and *AllBuy* and *AllSell* portfolios are 10.26% (p-value = 0.018) and 8.39% (p-value = 0.017) for the stocks in the smallest quintile and 6.88% (p-value = 0.000) and 5.07% (p-value = 0.108) for the stocks in the largest quintile. This is consistent with the notion that the overvaluation affects of opinion divergence should be strongest for stocks that are most costly to short. Small stocks are more expensive to trade in and are typically harder to borrow than are large stocks (see D'Avolio (2002)).

The managers look better in table 3 than they do in table 2. The *AllBuy* portfolio has higher returns than does the *AllSell* portfolio in four out of the five quintiles. However the only statistically significant differences are in quintile 3 (5.96%, p-value = 0.004) and quintile 2, which is negative (-4.89%, p-value = 0.009).

3.4. Sorting on Book-to-Market and Buy Proportion

Table 4 cross-sorts the trades in our sample on book-to-market ratios and divergence. The book values that we use in this paper are simply the book value of shareholder's common equity (COMPUSTAT Data60). We use book values as of July 2001. We calculate the book-to-market ratio by dividing each firm's book value by its market value on the day in which it first enters our sample (first day a stock has five or more in sample trades).

Table 4 reveals that the results we encountered in tables 1 and 2 were not driven by differences in book-to-market ratios. The U-shaped pattern, which we observed in the previous tables, holds up fairly consistently throughout the five book-to-market quintiles. However, the result is strongest with value stocks (quintile 5). The differences between the *Disagree* and *AllBuy* and *AllSell* portfolios are 21.13% (p-value = 0.000) and 16.92% (p-value = 0.000) for the stocks in the highest book-to-market quintile and -0.11% (p-value = 0.914) and 7.54% (p-value = 0.023) for the stocks in the lowest book-to-market quintile. These stocks in the high book-to-market quintile have an average book-to-market ratio of 1.12. Such a book-to-market ratio implies that a firm may be worth more if it were disassembled and sold off than if it were kept as a going concern. It could be that these firms are undergoing a period of financial distress and their prospects and thus values are hard to determine. Therefore, optimistic beliefs may be more inaccurate for these firms than for others.

3.5. Sorting on Momentum and Buy Proportion

The next portfolio strategy is designed to rule out the possibility that the momentum effect, first documented by Jegadeesh and Titman (1993), is causing our results. To form our momentum portfolios we sorted all of the stocks in our sample on their past returns measured from *t-1* to *t-12* (as in Fama and French (1996)). We calculate past returns from one month prior to the first day a stock enters our sample (first day with five or more trades). We then place each stock into one of the five portfolios based on its past return.

Table 5 displays the returns of the 25 portfolios. The U-shaped pattern emerges across all five momentum quintiles. All of the differences between the *Disagree* and *AllBuy* and *Disagree* and *AllSell* portfolios are large, and nine of the ten are statistically significant. The results also reveal that managers are perhaps more likely to make bad trading decisions than good ones. In quintiles 2, 4, and 5 the *AllSell* portfolios had significantly higher returns than did the *AllBuy* portfolios.

4. Regression Tests

In this section we use regressions to illustrate the relationships between opinion divergence and stock returns and manager skill and stock returns. The results in the last section imply that trading is uninformative when the funds in our sample trade in the same direction. Yet, we found that trading may predict returns when the funds in our sample trade against each other. We construct an opinion divergence measure that measures the level of disagreement among the funds that trade in the same stock on the same day in our sample. Our new measure treats homogenous trading the same regardless if the funds are all buying or all selling. We also interact our divergence measure with proxies for short sale constraints. By doing so, we hope to demonstrate that opinion divergence affects returns more strongly with stocks that are hard to short.

Our measure of disagreement in this section, *DIVERGENCE*, is constructed so that it is continuous and well suited for regression tests. To measure disagreement we count the number of trades of each stock on each day. As before, only stocks with five more or trades on a given day make it into our sample. We then divide the number of buys by the number of total trades and divide the number of sells by the number of total trades. The minimum of these two values is our *DIVERGENCE* measure. *DIVERGENCE* always takes on a value that is between 0 and 0.5. If all of the funds are either buying or selling *DIVERGENCE* will be equal to 0. If exactly half of the funds are buying and half are selling *DIVERGENCE* will equal 0.5. For example, let us say that Microsoft (MSFT) traded 10 times on one day and there were 7 buys and 3 sells. The number of buys divided by the total number of trades is 0.7, and the number of sells divided by the total number of trades is 0.3. Therefore, MSFT will have a *DIVERGENCE* value of 0.3 for that day.

The main control variables in our regressions are log of market value *LN(ME)*, log of book-to-market *LN(BE/ME)*, and past returns from *t-1* to *t-12 (MOM).*

We also introduce two interaction variables into our regressions. What drives the opinion divergence – low return relationship are short sale constraints. Miller's model implies that if the low returns we observe for high divergence stocks are the result of short sale constraints then this relationship should be stronger for stocks that are difficult to short. Our measures of short sale constraints are percentage of shares outstanding held by institutions (institutional holdings) and share price. In order to short a stock one must borrow the shares. Companies that have a large number of their shares owned by institutions are typically easier to borrow and thus less costly to short (see Dechow, Hutton, Meulbroek, and Sloan (2001) and D'Avolio (2002)). Stocks with low share prices tend to have wider bid ask spreads and larger price impacts. There is also empirical evidence that low price stocks can deter arbitrageurs (see Pontiff (1996)). Our interaction variables are *DIVERGENCE_INSTHLDS* and *DIVERGENCE_PRC*. *DIVERGENCE_INSTHLDS* is calculated as *DIVERGENCE* * (1 - institutional holdings) and *DIVERGENCE_PRC* is calculated as *DIVERGENCE* * (1/price).

4.1. Correlation Matrix

Table 6 reinforces our basic beliefs about the relationship between the independent variables and future returns. All three of the dispersions measures are negatively correlated to future returns. Consistent with other studies, *MOM* and *LN(BE/ME)* are positively correlated with future returns and *LN(ME)* is negatively correlated to future returns. Not surprisingly we also see that *DIVERGENCE, DIVERGENCE_INSTHLDS* and *DIVERGENCE_PRC* are all highly correlated with one another. *DIVERGENCE* has a correlation with *DIVERGENCE_INSTHLDS* of 0.75 and a correlation with *DIVERGENCE_PRC* 0.63. *DIVERGENCE_INSTHLDS* and *DIVERGENCE_PRC* have a correlation 0.51 with one another. To avoid any problems with multicollinearity we will not use these three variables in the same regression. Our *BUYPROPORTION* measure is calculated as in the previous sections, we just divide the number of buys on a given day by the total number of trades.

4.2. Regressions Tests

Table 7 shows the results of our regression tests. The dependent variable in all of the regressions is six-month market adjusted (r_{it} –r_{vw}) returns. Regressions 1 show that the relationship *BUYPROPORTION* is positive, but insignificant. Regressions 2 and 3 reveal that *DIVERGENCE* has a negative and significant relationship with returns the coefficients are -0.189 and -0.197; both p-values are 0.000.

In Regressions 5 and 6 we control for size, book-to-market and momentum and find that *DIVERGENCE* coefficient is still negative, but insignificant. However, in Regressions 7 and 8, where we interact *DIVERGENCE* with our short sale constraints price and institutional holdings, the divergence measures are now significant. In Regression 7 we replace *DIVERGENCE* with *DIVERGENCE_INSTHLDS*. By doing so we test the hypotheses that opinion divergence should have a stronger effect on the returns of stocks that are harder to short. The p-value for *DIVERGENCE_INSTHLDS* (0.001) is much smaller than is the p-value for *DIVERGENCE* Regression 6 (0.118). The magnitude of the coefficients of the two variables is not comparable. Regression 7 confirms our hypotheses that opinion divergence should have a stronger effect on the returns of stocks that are more difficult to short.

In Regression 8 we replace *DIVERGENCE* with *DIVERGENCE_PRC*. As theory predicts the coefficient for *DIVERGENCE_PRC* is negative and the p-value for *DIVERGENCE_PRC* (0.000) is much smaller than is the p-value for *DIVERGENCE* Regression 6 (0.118). The coefficients of the two variables are not comparable. The p-values however imply that the effect of opinion divergence on returns is stronger for stocks that have low stock prices, i.e. stocks that are costlier to short. The results here are consistent with those in Boehme, Danielsen, and Sorescu (2005), who use dispersion in analysts' forecasts as a proxy for opinion divergence and show that opinion divergence-return relationship only occurs in stocks that are difficult to short.

5. Intra-Family Analyses

In this section we define disagreement as something that occurs among managers at the *same fund family*, rather than among managers within our entire sample. Our unit of observation is now fund family/stock/date whereas before our unit of observation was stock/date.

An important difference here is that one stock may trade within multiple fund families on the same day. For example, MSFT may trade five times or more within three different fund families on the same day. Therefore, MSFT might have three different buy proportions on that day. If MSFT's buy proportions are significantly different from one another then it is possible that MSFT might be in three different opinion portfolios on the same day. Therefore, in order for our univariate results to hold stocks that trade within multiple fund families need to have similar buy proportions at each of the different families.

5.1. Intra-Family Portfolio Characteristics

For each of the trading days in our sample we take each stock that had at least five funds within a single fund family trading in it and calculate the same buy proportion measure and portfolio boundaries as we did in section 2. For example, let us say that 5 of the managers in Fund Company A buy MSFT and none sell MSFT. Then on that day MSFT gets placed in the *AllBuy* portfolio. If, on that same day, 5 managers at Fund Company B buy MSFT and 5 managers at B sell MSFT, then MSFT also gets placed in the *Disagree* portfolio.

Table 8 displays the frequency and average characteristics of the stocks in each of the different opinion portfolios. The first two columns in table 8 display the number and percentage of stock/date observations that fall into each of the different opinion portfolios. 16.2% of the observations fall into the *Disagree* portfolio versus 37.7% in table 1 when we measured across family. Not surprisingly, managers who work at the same fund family and presumably share information tend to agree more, although we still feel that 16.2%, or about 1 in 6 trades is a pretty good amount of disagreement.

As with across funds, it is more common for the managers in our sample to buy in unison than it is for them to sell in unison. The *MinSell* and *AllBuy* portfolios make up 15.3% and 33.4% of the sample, while the *MinBuy* and *AllSell* portfolio*s* make up only 12.2% and 22.9% of the sample.

The next 3 columns in table 8 explore the characteristics of the stocks in the different portfolios. The stocks in the *Disagree* portfolio have, on average, the largest market values (average is $57,528 million), the lowest book-to-market ratios (average is 0.37) and the lowest past returns (average is –5.57%) of the 5 opinion portfolios. This pattern is identical to the across family pattern, so interfamily disagreement ends to be in the same stocks as is across family disagreement.

5.2. Intra-Family Portfolio Returns Over Different Horizons

In table 9 we calculate future returns for 1,6, and 12-month holding periods. We calculate our portfolio returns and p-values the same way as described in the previous section. The results in this table are not consistent with the mangers in our sample possessing private information.

Table 9 shows that the *Disagree* portfolio has the lowest returns at every horizon. The difference between the *Disagree* portfolio's returns and the *AllBuy* portfolio's returns are 1.98%, 8.55% and 6.08% over 1, 6, and 12-month horizons. All of the differences are significant at the 99% level. The difference between the *Disagree* portfolio's returns and the *AllSell* portfolio's returns are 1.90%, 9.88% and –9.22% over 1, 6, and 12-month horizons. All of the differences are significant at the 99% level. These results are similar to those in table 2.

Table 9 also shows that the *MinBuy* and *MinSell* portfolios have lower returns than do the *AllBuy* and *AllSell* portfolios at every horizon. This pattern implies that as divergence in opinion increase returns begin to decrease, consistent with the hypotheses that opinion divergence coupled with short sale constraints will cause an upward bias in share prices and subsequent low returns. We plot these results in figure 2. As in table 2, table 9 provides no evidence of manager possessing private information. These results imply that our buy proportions are similar here to those calculated across families (in the last section). The results here also imply that stocks which trade at multiple families on the same day have similar buy proportions at each of the different families.

5.3. Intra-Family Regression Tests

As in the previous section the measure of disagreement in this section, *DIVERGENCE,* is constructed as a continuous variable. To measure disagreement we count the number of trades of each stock *within a fund family* on each day. As before, only stocks with five more or trades on a given day make it into our sample. We then divide the number of buys within a fund family by the number of total trades within a fund family and divide the number of sells within a fund family by the number of total trades within a family. The minimum of these two values is our *DIVERGENCE* measure. To avoid using repeated observations in our regressions we use an average of our within family *DIVERGENCE* measure for stocks' with multiple observations on the same day.

5.3.1. Intra-Family Correlation Matrix

Table 10 is a correlation matrix reinforces our previous results with respect to the relationship between our family level diversion measure and future returns. All of the diversion measures are negatively related to future returns. Not surprisingly we also see that *DIVERGENCE, DIVERGENCE_INSTHLDS* and *DIVERGENCE_PRC* are all highly correlated. *DIVERGENCE* has a correlation with *DIVERGENCE_INSTHLDS* of 0.87 and a correlation with *DIVERGENCE_PRC* 0.75. *DIVERGENCE_INSTHLDS* and *DIVERGENCE_PRC* have a correlation 0.68 with one another. To avoid any problems with multicollinearity we will not use these three variables in a single regression. Note that the correlation between *DIVERGENCE* and returns is -0.08, very close to the correlation of

DIVERGENCE and returns in table 6 of -0.07. This would imply that *DIVERGENCE* takes on similar values for the within and across family calculations.

5.3.2. Intra-Family Regressions

The Regressions in table 11 are like those in table 7, only the *DIVERGENCE* measures in table 11 is constructed at the family level, while the *DIVERGENCE* measure at in table 7 is constructed within the entire sample. The signs for all of the *DIVERGENCE* coefficients are negative and as in table 7 *DIVERGENCE_INSTHLDS* and *DIVERGENCE_PRC* have smaller *p-values* than does *DIVERGENCE*, which implies that opinion divergence has a stronger, more negative affect on the returns of stocks that are more difficult to short. The *p-values*, coefficients and R-squared in table 11 are similar to those in table 7. Our results imply that *DIVERGENCE* takes on similar values for the within and across family calculations. The results here also show that opinion divergence along with short sale constraint will cause an upward bias in stock prices and thus low returns.

The *BUYPROPORTION* is negative and insignificant throughout all of the regressions. If managers did in fact share correlated private information we would especially expect to see this happen among managers that are working at the same fund family. The results here reinforce our early conclusion that mangers do not possess such information.

6. Conclusion

In this paper we document the extent of disagreement among fund managers who are trading in the same stock on the same day. We measure manager disagreement both across and within fund families. We document that manager disagreement, even among mangers working at the same fund company, is commonplace.

We show that disagreement among managers occurs in different types of stocks than it does with analysts. However, like disagreement among analysts, disagreement among managers can predict the cross-section of stock returns. Our results are consistent with the hypotheses that opinion divergences coupled with short sale constraints will lead to an upward bias in share prices and subsequent low returns. We show that this result holds true when divergence is measured as disagreement within our entire sample of funds or as disagreement among funds within individual fund families. We show that returns are especially low for stocks that have high heterogeneity in trading and high short sale costs and constraints.

Lastly, we reject the notion that professional investment managers possess stock picking ability or private information that is of investment value. When trading is homogeneous among professional investment managers, we find that returns are roughly the same regardless if the managers in our sample are all buying or all selling.

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Table 1. Opinion Portfolio Frequencies and Characteristics

This table presents opinion portfolio frequencies and characteristics for 5 opinion portfolios. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. Both the number (N) and percentage (% of N) of observations in each of the 5 opinion portfolios are reported. Portfolio characteristics include average Size (ME, market value of equity), Book-to-Market (BE/ME, book value of equity/market value of equity), and Momentum (MOM, the return from 12 month ago to 1 month ago). The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION as the number of funds buying that stock on that day divided by the total number of funds buying and selling that stock on that day. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio.

	N	% of N	ME ($M)	BE/ME	MOM
AllSell	1,860	5.8%	2,702	0.64	6.37%
MinBuy	4,757	14.9%	10,779	0.48	0.54%
Disagree	12,027	37.7%	26,498	0.39	-4.25%
MinSell	8,710	27.3%	19,458	0.41	0.53%
AllBuy	4,521	14.2%	4,257	0.52	11.31%
Total	31,875		17,685	0.44	0.60%

Table 2. Opinion Portfolio Returns Over Different Horizons

This table presents equal-weighted portfolio returns over 1, 6 and 12-month horizons for 5 opinion portfolios. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION as the number of funds buying that stock on that day divided by the total number of funds buying and selling that stock on that day. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then reported. P-values, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors with twenty lags. Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	1 Month	**6 Month**	**12 Month**
AllSell	4.00%	11.78%	8.15%
MinBuy	1.65%	5.04%	0.39%
Disagree	1.46%	2.24%	-2.29%
MinSell	1.85%	3.84%	-1.17%
AllBuy	4.31%	11.27%	3.79%
Total	2.21%	5.08%	0.01%
AllBuy - AllSell	0.31%	-0.51%	-4.36%
	(0.638)	(0.346)	(0.005)***
AllBuy - Disagree	2.85%	9.03%	6.08%
	(0.000)***	(0.000)***	(0.000)***
AllSell - Disagree	2.54%	9.54%	10.44%
	(0.000)***	(0.000)***	(0.000)***

Table 3. Size and Opinion Portfolio Returns

This table presents equal-weighted 6-month portfolio returns for 5 opinion portfolios, sorted into Size (ME, market value of equity) quintiles. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. Each ME quintile contains the same number of stocks. The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION as the number of funds buying that stock on that day divided by the total number of funds buying and selling that stock on that day. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then reported. P-values, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors with twenty lags. Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	ME Quintiles				
	1-Small	**2**	**3**	**4**	**5-Large**
ME ($ M)	331	795	1,630	3,677	37,050
AllSell	14.19%	19.27%	4.49%	8.96%	5.87%
MinBuy	10.53%	15.00%	6.45%	2.12%	2.83%
Disagree	5.89%	8.69%	6.34%	1.28%	0.82%
MinSell	13.66%	11.07%	9.19%	2.81%	1.52%
AllBuy	15.96%	14.18%	10.45%	10.64%	7.79%
Total	13.61%	13.40%	8.21%	3.64%	1.84%
AllBuy - AllSell	1.83%	-4.89%	5.96%	1.68%	2.21%
	(0.517)	(0.009)***	(0.004)***	(0.389)	(0.436)
AllBuy - Disagree	10.26%	5.71%	4.32%	9.36%	6.88%
	(0.018)**	(0.006)***	(0.033)**	(0.001)***	(0.000)***
AllSell - Disagree	8.39%	10.05%	-1.66%	7.68%	5.07%
	(0.017)**	(0.000)***	(0.631)	(0.000)***	(0.108)

Table 4. Book-to-Market and Opinion Portfolio Returns

This table presents equal-weighted 6-month portfolio returns for 5 opinion portfolios, sorted into Book-to-Market (BE/ME, book value of equity/market value of equity) quintiles. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. Each BE/ME quintile contains the same number of stocks. The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION as the number of funds buying that stock on that day divided by the total number of funds buying and selling that stock on that day. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then reported. P-values, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors with twenty lags. Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	BE/ME Quintiles				
	1-Low	**2**	**3**	**4**	**5-High**
BE/ME	0.13	0.27	0.43	0.59	1.12
AllSell	6.62%	8.12%	8.00%	19.84%	12.20%
MinBuy	1.76%	5.26%	2.90%	13.71%	1.84%
Disagree	-1.04%	3.12%	4.94%	9.66%	-4.71%
MinSell	-0.78%	3.34%	6.34%	12.33%	1.46%
AllBuy	-1.15%	7.83%	12.27%	21.82%	16.42%
Total	-0.17%	4.23%	6.85%	13.75%	3.58%
AllBuy - AllSell	-8.00%	-0.25%	4.27%	1.99%	4.21%
	(0.046)**	(0.942)	(0.167)	(0.369)	(0.025)**
AllBuy - Disagree	-0.11%	4.71%	7.33%	12.16%	21.13%
	(0.914)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
AllSell - Disagree	7.54%	4.95%	3.06%	10.17%	16.92%
	(0.023)**	(0.121)	(0.388)	(0.000)***	(0.000)***

Table 5. Momentum and Opinion Portfolio Returns

This table presents equal-weighted 6-month portfolio returns for 5 opinion portfolios, sorted into Momentum (MOM) quintiles. MOM is the return from 12 month ago to 1 month ago. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. Each MOM quintile contains the same number of stocks. The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION as the number of funds buying that stock on that day divided by the total number of funds buying and selling that stock on that day. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then reported. P-values, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors with twenty lags. Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	MOM Quintiles				
	1-Low	**2**	**3**	**4**	**5-High**
MOM	-52.10%	-15.85%	1.31%	17.58%	63.66%
AllSell	-5.19%	13.17%	10.66%	25.56%	19.49%
MinBuy	-13.33%	5.53%	8.50%	13.73%	13.76%
Disagree	-14.19%	-0.22%	7.99%	11.87%	11.29%
MinSell	-12.58%	1.83%	7.82%	12.25%	11.78%
AllBuy	-2.22%	3.95%	15.35%	20.66%	15.18%
Total	-11.97%	2.04%	9.41%	14.55%	13.47%
AllBuy - AllSell	2.61%	-9.26%	5.10%	-4.85%	-4.26%
	(0.263)	(0.000)***	(0.021)**	(0.051)*	(0.000)***
AllBuy - Disagree	11.97%	4.16%	7.37%	8.78%	3.88%
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
AllSell - Disagree	9.19%	13.33%	2.71%	13.59%	8.21%
	(0.000)***	(0.000)***	(0.211)	(0.000)***	(0.000)***

Table 6. Correlation Matrix

This table presents the correlation matrix of different variables. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We also obtain institutional holdings data from Thomson Financial CDA/Spectrum Institutional Holdings (13f)) database. 6-Month Market-Adjusted Return is 6-month raw return minus the return on the CRSP value-weighted index. LN(ME) is the natural logarithm of market value of equity. LN(BE/ME) is the natural logarithm of the ratio of book value of equity divided by market value of equity. MOM is the return from 12 month ago to 1 month ago. The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION (SELLPROPORTION) as the number of funds buying (selling) that stock on that day divided by the total number of funds buying and selling that stock on that day. DIVERGENCE is defined as the minimum of BUYPROPORTION and SELLPROPORTION. DIVERGENCE_INSTHLDS is defined as DIVERGENCE * (1 - institutional holdings). DIVERGENCE_PRC is defined as DIVERGENCE * (1/price).

	6 Month Market-Adjusted Return	LN(ME)	LN(BE/ME)	MOM	BUYPROPORTION	DIVERGENCE	DIVERGENCE_INSTHLDS
LN(ME)	-0.18						
LN(BE/ME)	0.15	-0.30					
MOM	0.20	-0.15	-0.08				
BUYPROPORTION	0.01	0.01	-0.04	0.04			
DIVERGENCE	-0.09	0.38	-0.13	-0.10	-0.23		
DIVERGENCE_INSTHLDS	-0.13	0.39	-0.06	-0.12	-0.17	0.75	
DIVERGENCE_PRC	-0.10	-0.01	0.16	-0.20	-0.17	0.63	0.51

Table 7. Regression Analysis

This table presents regression results. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We also obtain institutional holdings data from Thomson Financial CDA/Spectrum Institutional Holdings (13f)) database. The dependent variable is 6-Month Market-Adjusted Return: 6-month raw return minus the return on the CRSP value-weighted index. The definitions of independent variables are as follows. LN(ME) is the natural logarithm of market value of equity. LN(BE/ME) is the natural logarithm of the ratio of book value of equity divided by market value of equity. MOM is the return from 12 month ago to 1 month ago. The unit of observation is stock/date. We exclude observations with less than 5 fund trades. For each stock/date, we define BUYPROPORTION (SELLPROPORTION) as the number of funds buying (selling) that stock on that day divided by the total number of funds buying and selling that stock on that day. DIVERGENCE is defined as the minimum of BUYPROPORTION and SELLPROPORTION. DIVERGENCE_INSTHLDS is defined as DIVERGENCE * (1 - institutional holdings). DIVERGENCE_PRC is defined as DIVERGENCE * (1/price). Robust p-values, which are in parentheses, are adjusted for heteroskedasticity and serial correlation by clustering on stocks (PERMNO). Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.048	0.095	0.107	0.600	0.579	0.579	0.515	0.637
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LN(ME)				-0.022	-0.021	-0.021	-0.017	-0.022
				(0.000)***	(0.001)***	(0.001)***	(0.005)***	(0.000)***
LN(BE/ME)				0.051	0.050	0.050	0.052	0.056
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
MOM				0.124	0.123	0.123	0.122	0.112
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
BUYPROPORTION	0.006		-0.018	0.005		-0.000		
	(0.716)		(0.304)	(0.767)		(0.999)		
DIVERGENCE		-0.189	-0.197		-0.040	-0.040		
		(0.000)***	(0.000)***		(0.104)	(0.118)		
DIVERGENCE_INSTHLDS							-0.264	
							(0.001)***	
DIVERGENCE_PRC								-3.273
								(0.000)***
Adjusted R-squared	0.000	0.009	0.009	0.076	0.077	0.077	0.079	0.085

Table 8. Intra-Family Opinion Portfolio Frequencies and Characteristics

This table presents opinion portfolio frequencies and characteristics for 5 intra-family opinion portfolios. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. Both the number (N) and percentage (% of N) of observations in each of the 5 opinion portfolios are reported. Portfolio characteristics include average Size (ME, market value of equity), Book-to-Market (BE/ME, book value of equity/market value of equity), and Momentum (MOM, the return from 12 month ago to 1 month ago). The unit of observation is fund family/stock/date. We exclude observations with less than 5 fund trades. For each fund family/stock/date, we define BUYPROPORTION as the number of funds within that fund family buying that stock on that day divided by the total number of funds within that fund family buying and selling that stock on that day. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio.

	N	% of N	ME ($M)	BE/ME	MOM
AllSell	5,020	22.9%	14,589	0.50	-0.19%
MinBuy	2,679	12.2%	39,327	0.43	-5.26%
Disagree	3,538	16.2%	57,258	0.37	-5.57%
MinSell	3,345	15.3%	40,370	0.39	-4.06%
AllBuy	7,324	33.4%	17,456	0.45	3.65%
Total	21,906		29,401	0.44	-0.99%

Table 9. Intra-Family Opinion Portfolio Returns Over Different Horizons

This table presents equal-weighted portfolio returns over 1, 6 and 12-month horizons for 5 intra-family opinion portfolios. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. The initial unit of observation is fund family/stock/date. We exclude observations with less than 5 fund trades. For each fund family/stock/date, we define BUYPROPORTION as the number of funds within that fund family buying that stock on that day divided by the total number of funds within that fund family buying and selling that stock on that day. We then compute the average BUYPROPORTION across different fund families for the same stock/date. Hence the unit of observation becomes stock/date. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then reported. P-values, which are in parentheses, are adjusted for serial correlation using Newey-West standard errors with twenty lags. Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	1 Month	6 Month	12 Month
AllSell	2.92%	9.32%	4.81%
MinBuy	1.27%	1.42%	-2.52%
Disagree	1.02%	-0.56%	-4.42%
MinSell	1.46%	0.88%	-3.62%
AllBuy	3.00%	7.99%	1.66%
Total	2.23%	4.86%	-0.04%
AllBuy - AllSell	0.07%	-1.34%	-3.14%
	(0.899)	(0.273)	(0.022)**
AllBuy - Disagree	1.98%	8.55%	6.08%
	(0.000)***	(0.000)***	(0.000)***
AllSell - Disagree	1.90%	9.88%	9.22%
	(0.000)***	(0.000)***	(0.000)***

Table 10. Intra-Family Correlation Matrix

This table presents the correlation matrix of different variables at the intra-family level. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We also obtain institutional holdings data from Thomson Financial CDA/Spectrum Institutional Holdings (13f)) database. 6-Month Market-Adjusted Return is 6-month raw return minus the return on the CRSP value-weighted index. LN(ME) is the natural logarithm of market value of equity. LN(BE/ME) is the natural logarithm of the ratio of book value of equity divided by market value of equity. MOM is the return from 12 month ago to 1 month ago. The initial unit of observation is fund family/stock/date. We exclude observations with less than 5 fund trades. For each fund family/stock/date, we define BUYPROPORTION (SELLPROPORTION) as the number of funds within that fund family buying (selling) that stock on that day divided by the total number of funds within that fund family buying and selling that stock on that day. DIVERGENCE is defined as the minimum of BUYPROPORTION and SELLPROPORTION. We then compute the average BUYPROPORTION and DIVERGENCE across different fund families for the same stock/date. Hence the unit of observation becomes stock/date. DIVERGENCE_INSTHLDS is defined as DIVERGENCE * (1 - institutional holdings). DIVERGENCE_PRC is defined as DIVERGENCE * (1/price).

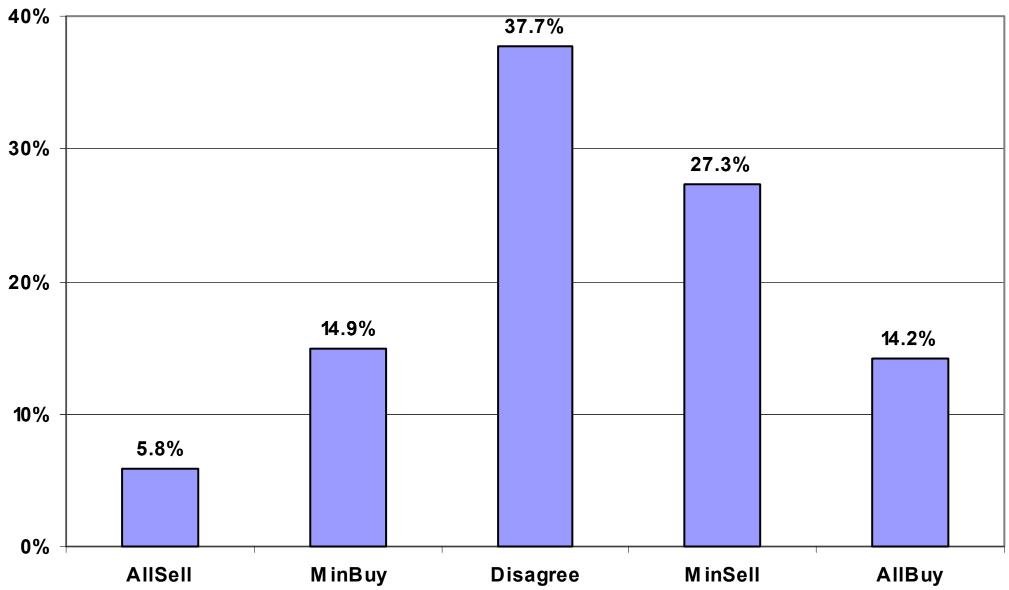
	6 Month Market-Adjusted Return	**LN(ME)**	**LN(BE/ME)**	**MOM**	**BUYPROPORTION**	**DIVERGENCE**	**DIVERGENCE _INSTHLDS**
LN(ME)	-0.22						
LN(BE/ME)	0.16	-0.34					
MOM	0.19	-0.18	-0.07				
BUYPROPORTION	-0.01	-0.02	-0.05	0.03			
DIVERGENCE	-0.08	0.33	-0.11	-0.07	-0.08		
DIVERGENCE_INSTHLDS	-0.10	0.37	-0.08	-0.09	-0.07	0.87	
DIVERGENCE_PRC	-0.07	0.08	0.09	-0.12	-0.06	0.75	0.68

Table 11. Intra-Family Regression Analysis

This table presents intra-family regression results. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We also obtain institutional holdings data from Thomson Financial CDA/Spectrum Institutional Holdings (13f)) database. The dependent variable is 6-Month Market-Adjusted Return: 6-month raw return minus the return on the CRSP value-weighted index. The definitions of independent variables are as follows. LN(ME) is the natural logarithm of market value of equity. LN(BE/ME) is the natural logarithm of the ratio of book value of equity divided by market value of equity. MOM is the return from 12 month ago to 1 month ago. The initial unit of observation is fund family/stock/date. We exclude observations with less than 5 fund trades. For each fund family/stock/date, we define BUYPROPORTION (SELLPROPORTION) as the number of funds within that fund family buying (selling) that stock on that day divided by the total number of funds within that fund family buying and selling that stock on that day. DIVERGENCE is defined as the minimum of BUYPROPORTION and SELLPROPORTION. We then compute the average BUYPROPORTION and DIVERGENCE across different fund families for the same stock/date. Hence the unit of observation becomes stock/date. DIVERGENCE_INSTHLDS is defined as DIVERGENCE * (1 - institutional holdings). DIVERGENCE_PRC is defined as DIVERGENCE * (1/price). Robust p-values, which are in parentheses, are adjusted for heteroskedasticity and serial correlation by clustering on stocks (PERMNO). Statistical significance is indicated by *** for one percent level, ** for five percent level, and * for ten percent level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.055	0.069	0.077	0.723	0.706	0.712	0.675	0.706
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LN(ME)				-0.028	-0.027	-0.027	-0.025	-0.026
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LN(BE/ME)				0.046	0.047	0.046	0.047	0.049
				(0.004)***	(0.003)***	(0.004)***	(0.003)***	(0.002)***
MOM				0.108	0.108	0.108	0.108	0.105
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
BUYPROPORTION	-0.008		-0.013	-0.010		-0.011		
	(0.628)		(0.424)	(0.528)		(0.507)		
DIVERGENCE		-0.187	-0.189		-0.020	-0.022		
		(0.000)***	(0.000)***		(0.572)	(0.528)		
DIVERGENCE_INSTHLDS							-0.168	
							(0.052)*	
DIVERGENCE_PRC								-2.548
								(0.040)**
Adjusted R-squared	0.000	0.006	0.007	0.082	0.081	0.082	0.082	0.084

Panel A. Opinion Portfolio Frequencies.



Panel B. Opinion Portfolio Returns Over Different Horizons.

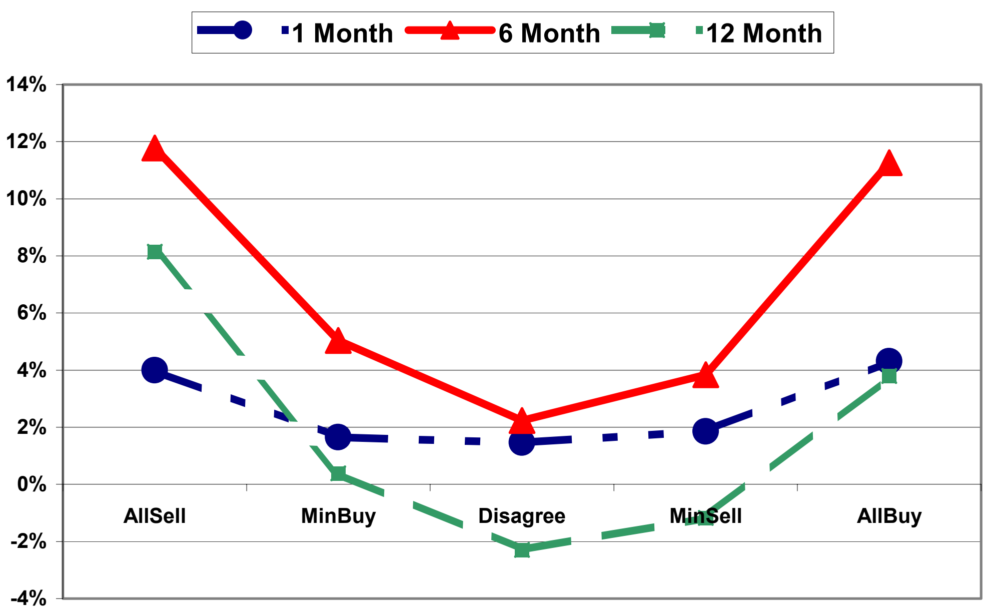
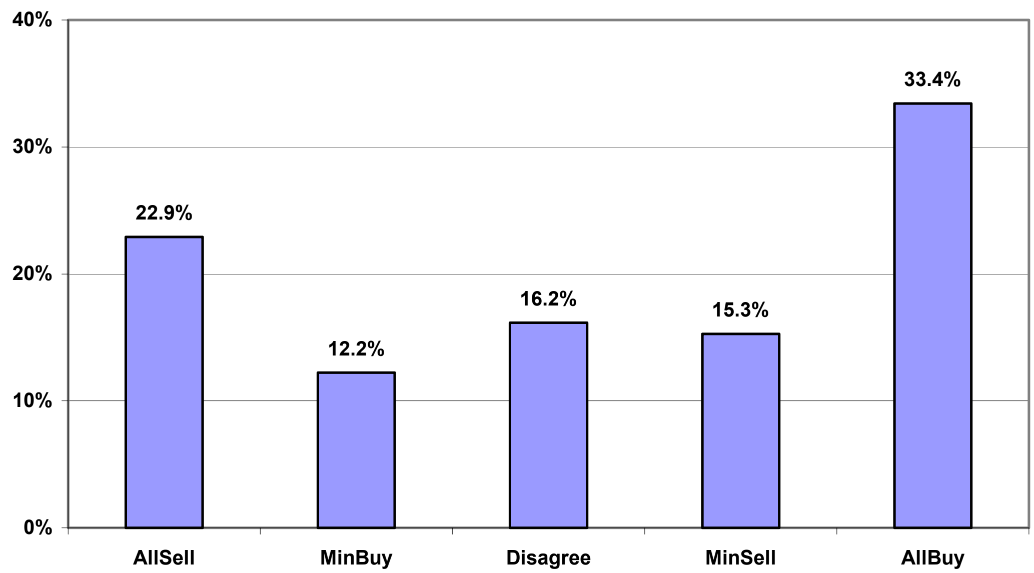


Figure 1. Opinion Portfolio Frequencies and Returns. Panel A of this figure plots frequencies of 5 opinion portfolios, as reported in table 1. Panel B of this figure plots equal-weighted portfolio returns over 1, 6 and 12-month horizons for 5 opinion portfolios, as reported in table 2. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then plotted.

Panel A. Intra-Family Opinion Portfolio Frequencies.



Panel B. Intra-Family Opinion Portfolio Returns Over Different Horizons.

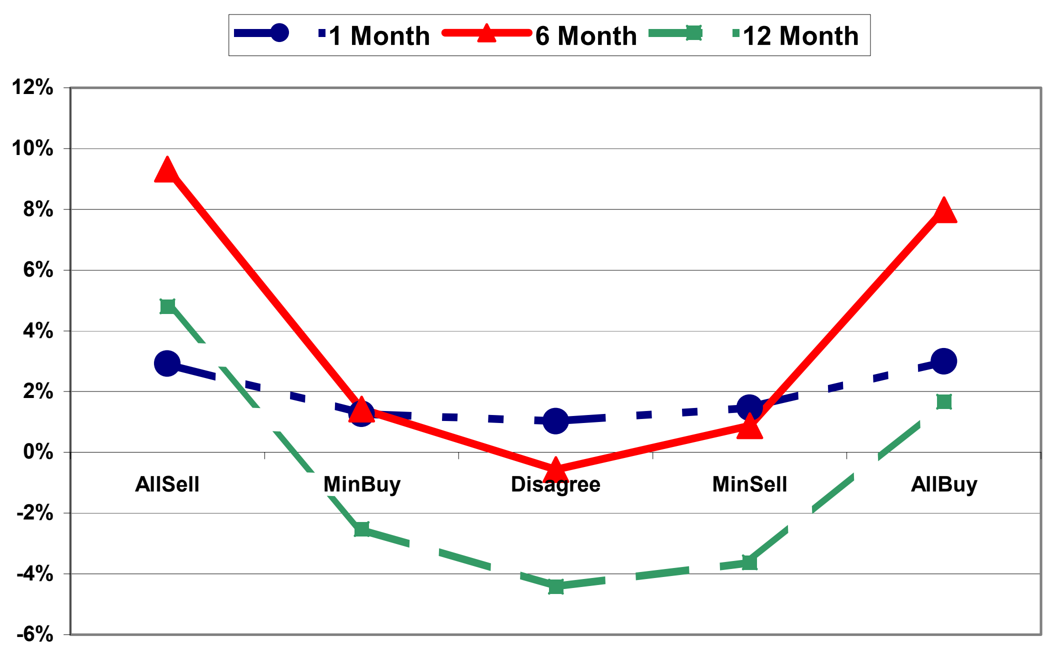


Figure 2. Intra-Family Opinion Portfolio Frequencies and Returns. Panel A of this figure plots frequencies of 5 intra-family opinion portfolios, as reported in table 8. Panel B of this figure plots equal-weighted portfolio returns over 1, 6 and 12-month horizons for 5 intra-family opinion portfolios, as reported in table 9. Our sample includes proprietary transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $ 412 billion traded. We obtain prices, returns, and shares outstanding from CRSP. We exclude stocks with prices less than $5.00. We obtain book values of equity from COMPUSTAT (Data60). We exclude stocks with negative book values of equity. We put observations with BUYPROPORTION = 0 into the AllSell portfolio, observations with 0 < BUYPROPORTION <= 0.3 into the MinBuy (Minority Buying) portfolio, observations with 0.3 < BUYPROPORTION <= 0.7 into the Disagree portfolio, observations with 0.7 < BUYPROPORTION < 1 into the MinSell portfolio, and finally observations with BUYPROPORTION = 1 into the AllBuy portfolio. Returns are market-adjusted: raw returns minus the returns on the CRSP value-weighted index. Returns are first averaged across different stocks on each trade date. Time series averages over trade dates are then plotted.