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Opinion Divergence Among Professional Investment Managers

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Abstract: We find that opinion divergence among professional investment managers is commonplace, using a large sample of 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.

Keywords: opinion divergence, short-sale constraints, institutional trading, return predictability, stock picking ability, private information

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

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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 et al. (1992) and Hirshleifer et al. (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 manager 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 trade against the crowd they ought to have extremely good information, as going against the crowd is risky. 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. In Miller's framework, it is especially important to study how opinion divergence among institutional investors affects stock returns, because 'institutional investors play a price-setting role' (Gibson and Safieddine, 2003).

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 et al. (2000)

1 Harrison and Kreps (1978), Diamond and Verrecchia (1987), Morris (1996), Chen et al. (2002), Duffie et al. (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.

use changes in quarterly and/or semiannual fund holdings as a *trade 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 changes 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 et al. (2002) and Boehme et al. (2006) 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. We show that opinion divergence among fund managers occurs in different types of stocks than it does with analysts.

Chen et al. (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 et al. (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 presumably sharing the same information. We measure disagreement using a simple buy proportion. For example, if there is \$5 million of buying in Microsoft on a given day, and \$5 million of selling in Microsoft on that same day, then Microsoft's buy proportion is buys/(buys + sells) = 5/10 = 0.5 on that day.[6] We find that 22.5% of our stock-day observations have an across family buy proportion

3 Gibson et al. (2004) find that institutions make profitable investments in companies that are having SEO's. Baker et al. (2004) find that managers can pick stocks around earnings announcements.

4 Recent papers by Ghysels and Juergens (2001), Cao et al. (2003), Liu et al. (2003), Johnson (2004) and Qu et al. (2004) contend that the relationship between analyst forecast dispersion and future returns can be explained by factors other than opinion divergences and optimistic valuations.

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

6 The results of our analysis are similar when the number of funds (instead of the dollar value of trades) is used to construct measures of trading activity.

that is between 0.3 and 0.7, which we interpret as a range of substantial opinion divergence.

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 et al. (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 '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.[7] 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.[8]

We do find that returns 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 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.[9]

Finally, it is important to note that the negative relationship between opinion divergence and future stock returns documented by us cannot be used to devise profitable trading strategies, because our dataset is not publicly available to market participants. In fact, our sample institutional investors do not even know each other's trades, and hence they cannot construct the same measures we computed. Also, the data were only made available to us with a long time-lag.

7 Gibson et al. (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 et al. (1997) and Ferson and Khang (2002) also imply that fund managers do not possess extraordinary investment abilities.

8 Chen et al. (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 et al. (2007) find that Chen et al.'s results become much weaker or nonexistent out of sample (post-1995), and in this paper we examine trades that occurred in 2001.

9 See also Thomas (2006) for a discussion, and Ali et al. (2003) for related findings on the book-to-market anomaly.

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. 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 (see, e.g., Keim and Madhavan, 1995). Goldstein et al. (2007) use 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 value 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 fund families would be removed from the data. However, identification codes were provided enabling us to separately identify them.[11]

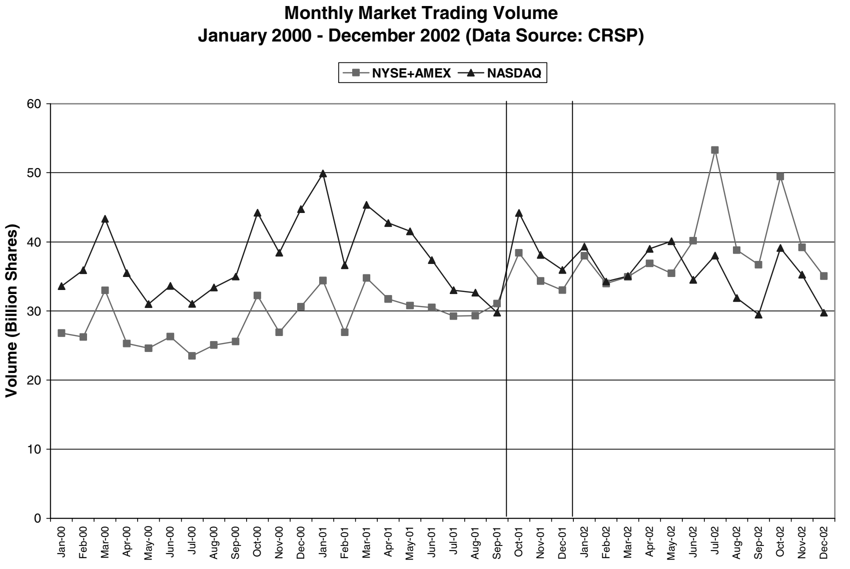
Our sample period is from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks. These trades originated from 1,730 different funds and 30 different fund families. There were a total of 15 billion shares or $412 billion traded. The general market trend is mildly bullish during this period. Since our paper mainly considers the trading activity of professional investment managers, we review the propriety of our sample period by examining whether there was anything unusual about trading volume in the market during this period relative to other periods. Specifically, we compare the NYSE/AMEX and NASDAQ volumes during our sample period against volumes during the three years surrounding the sample period, from January 2000 to December 2002. Figure 1 plots general market trading volumes over time and reveals no discernible differences for our three month sample period compared against any other quarter.

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.

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.

11 One limitation of the dataset is that it does not contain information on fund investment styles. We note that investment styles are important in determining how managers trade. At least some of the disagreement among managers could be potentially attributed to different investment styles, though it is not immediately clear how this would impact the tests of our main hypothesis: opinion divergence among managers would cause upward biases in stock prices, especially for those stocks that are difficult to short.

Figure 1



Notes:
This figure plots the monthly total shares (in billions) traded in the US stock market, for NYSE/AMEX and NASDAQ separately. The area in between the two vertical lines is our sample period, from October 2001 to December 2001. The data is from CRSP.

3. GROUP ANALYSIS

In this section we assign stocks to groups based on certain characteristics, and then draw conclusions about the differences in average returns or characteristics among the groups. 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.[12] For each stock/date, we define a buy proportion measure as the dollar value for buying in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. Once the buy proportion measure is calculated we place each stock into one of five opinion groups. If the buy proportion measure is equal to 1, we place the stock in the *AllBuy* group. If the buy proportion measure is equal to 0, we place the stock in the *AllSell* group. If our buy proportion measure is less than 1 but greater than 0.7, we place the stock in the *MinSell* (Minority Selling) group. If our buy proportion measure is less than 0.3 but greater than 0, we place the stock in the *MinBuy* (Minority Buying) group. Finally, if our buy proportion measure is less than 0.7 but greater than 0.3, we place the stock in the *Disagree* group.[13] All of the returns are market-adjusted by subtracting the return of the value weighted CRSP index.

12 We chose five managers because this is often the minimal number of managers used in the herding literature (see, e.g., Lakonishok et al., 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.
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* group. The results are similar.

(i) Group Characteristics

Table 1 displays the frequency and characteristics of the stocks in each of the different opinion groups. The first two columns in Table 1 display the number and percentage of stock-day observations that fall into each of the different opinion groups. 22.5% of the observations fall into the *Disagree* group; this is the most common group 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 *AllBuy* group makes up 14.2% of the sample, while the *AllSell* group makes up only 5.8% of the sample. These group frequencies are plotted in Figure 2, Panel A.

The next 3 columns in Table 1 explore the characteristics of the stocks in the different groups. The stocks in the *Disagree* group have, on average, the largest market values (average is $23,889 million), the lowest book-to-market ratios (average is 0.41) and the lowest past returns (average is −2.00%) of the five opinion groups. Diether et al. (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 groups in which the managers are trading together tend to be smaller, with higher book-to-market ratios. The *AllBuy* group has very high past returns, and implies momentum trading. These findings are consistent with Wermers (1999) who finds that herding is more prevalent among growth funds and in small stocks. Wermers also finds evidence of institutional momentum trading.

Table 1

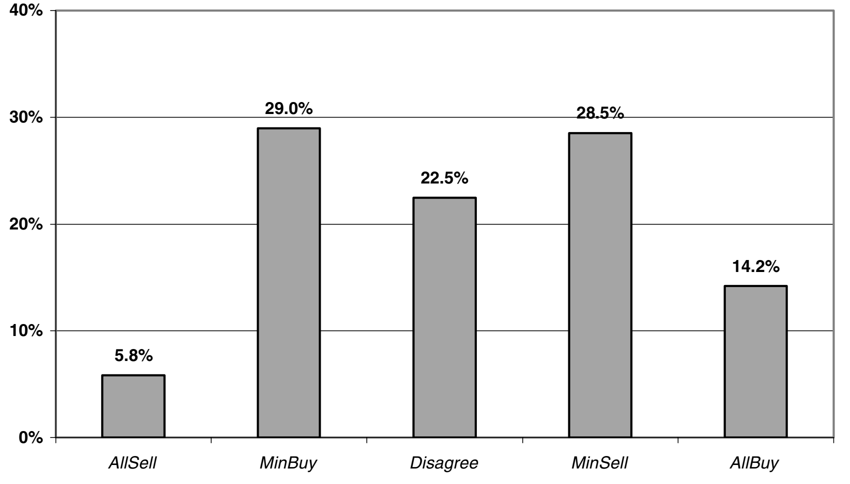
Opinion Group Frequencies and Characteristics

	N	*% of N*	*ME ($M)*	*BE/ME*	*MOM*
AllSell	1,860	5.8%	2,702	0.64	6.37%
MinBuy	9,236	29.0%	19,054	0.43	−1.37%
Disagree	7,165	22.5%	23,889	0.41	−2.00%
MinSell	9,093	28.5%	21,148	0.41	−1.86%
AllBuy	4,521	14.2%	4,257	0.52	11.31%
Total	31,875		17,685	0.44	0.60%

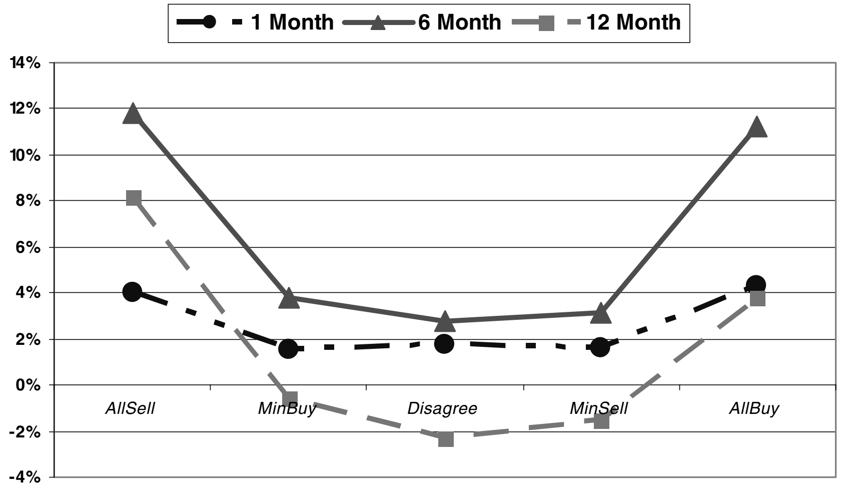
Notes:
This table presents opinion group frequencies and characteristics for five opinion groups. Our sample includes transaction-level institutional trading data from October 1, 2001 to December 31, 2001. Our sample is comprised of 553,580 daily trades of 4,171 different stocks, which originated from 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 five opinion groups are reported. Group 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 months ago to one month ago). The unit of observation is stock/date. We exclude observations with less than five fund trades. For each stock/date, we define BUYPROPORTION as the dollar value for buying in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. We put observations with BUYPROPORTION = 0 into the *AllSell* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group.

Figure 2

Panel A. Opinion Group Frequencies



Panel B. Opinion Group Returns Over Different Horizons



Notes:
Panel A of this figure plots frequencies of five opinion groups, as reported in Table 1. Panel B of this figure plots equal-weighted group returns over 1, 6 and 12-month horizons for five opinion groups, as reported in Table 2. Our sample includes 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* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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.

(ii) *Group Returns Over Different Horizons*

In Table 2 we calculate future returns for 1, 6 and 12-month holding periods. To calculate our group returns, we form groups on each day, and calculate the future returns of that group. 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 groups. The returns are market-adjusted, as we subtract the value-weighted return of the market from the return of each stock before the groups 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 et al. (1992) and Hirshleifer et al. (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* groups beat the *AllBuy* groups at the 6 and 12-month horizons by 0.51% (*p*-value = 0.346) and 4.36% (*p*-value = 0.005). At the 1-month horizon the *AllBuy* group beat the *AllSell* group by only 0.31%

Table 2

Opinion Group Returns Over Different Horizons

	1 Month	*6 Month*	*12 Month*
AllSell	4.00%	11.78%	8.15%
MinBuy	1.54%	3.82%	−0.55%
Disagree	1.75%	2.75%	−2.29%
MinSell	1.59%	3.18%	−1.51%
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	2.56%	8.51%	6.08%
	(0.000)***	(0.000)***	(0.000)***
AllSell – Disagree	2.25%	9.03%	10.44%
	(0.000)***	(0.000)***	(0.000)***

Notes:
This table presents equal-weighted group returns over 1, 6 and 12-month horizons for five opinion groups. Our sample includes 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 five fund trades. For each stock/date, we define BUYPROPORTION as the dollar value for buying in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. We put observations with BUYPROPORTION = 0 into the *AllSell* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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 the 1% level, ** for the 5% level, and * for the 10% level.

(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 on average had they not traded.

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 risky. 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* group should have the highest returns and the *MinSell* group should have the lowest returns. In the *Minbuy* group the buyers are in the minority, but the returns of this group are low relative to the others, so it does not seem that the buyers here possess any private information. In the *Minsell* group, the sellers are in the minority. The returns of this group are relatively low, however, the returns are similar to those of the *MinBuy* group and are larger than those of the *Disagree* group. This pattern does not support the notion that managers in our sample have private information.

Table 2 shows that the *Disagree* group has the lowest returns at every horizon. The difference between the *Disagree* group's returns and the *AllBuy* group's returns are 2.56%, 8.51% 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* group's returns and the *AllSell* group's returns are 2.25%, 9.03% 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* groups have lower returns than do the *AllBuy* and *AllSell* groups 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, Panel B, which displays a U-shaped pattern. Given that our results are robust and similar at 1, 6 and 12-month horizons, we will focus on 6-month returns in later analysis.

(iii) 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 groups we sort all of the stocks, which traded five or more times on at least one day, on their market values of equity (ME). We then placed our stocks in one of five size quintiles based on their size ranking. The average size of the stocks of each group and the number of trades within each group are also displayed. The averages reveal that there is a good deal of variation in the market values within our sample. The stocks that are 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 2 is consistent across the size quintiles. The *Disagree* groups returns are mostly lower than are those of both the *AllBuy* and the *AllSell* groups in each of the five size quintiles. In some of the size quintiles, the managers did better in terms of stock picking. The *AllBuy* group has higher returns than does the *AllSell* group 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).

Table 3
Size and Opinion Group Returns

	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	7.72%	9.31%	8.06%	2.51%	2.35%
Disagree	9.74%	14.48%	6.84%	1.54%	−0.17%
MinSell	12.42%	10.83%	7.60%	2.42%	1.31%
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	6.39%	−0.30%	3.61%	9.10%	7.97%
	(0.111)	(0.904)	(0.021)**	(0.000)***	(0.000)***
AllSell – Disagree	4.16%	3.83%	−2.35%	7.42%	6.05%
	(0.225)	(0.067)*	(0.380)	(0.000)***	(0.047)**

Notes:
This table presents equal-weighted 6-month group returns for five opinion groups, sorted into Size (ME, market value of equity) quintiles. Our sample includes 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 five fund trades. For each stock/date, we define BUYPROPORTION as the dollar value for buying in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. We put observations with BUYPROPORTION = 0 into the *AllSell* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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 the 1% level, ** for the 5% level, and * for the 10% level.

(iv) 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.

Table 4 reveals that the results we encountered in Table 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. The results are the strongest with value stocks (quintile 5). The differences between the *Disagree* and *AllBuy* and *AllSell* groups are 16.64% (p-value = 0.000) and 12.42% (p-value = 0.000) for the stocks in the highest book-to-market quintile and −0.12% (p-value = 0.897) and 7.61% (p-value = 0.024) 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

Table 4
Book-to-Market and Opinion Group Returns

	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	−0.08%	5.16%	4.07%	11.71%	−1.12%
Disagree	−1.03%	2.41%	4.57%	10.85%	−0.22%
MinSell	−0.48%	2.92%	6.75%	11.15%	−3.96%
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	−0.12%	5.41%	7.70%	10.98%	16.64%
	(0.897)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
AllSell – Disagree	7.61%	5.45%	3.43%	8.99%	12.42%
	(0.024)***	(0.086)*	(0.328)	(0.000)***	(0.000)***

Notes:
This table presents equal-weighted 6-month group returns for five opinion groups, sorted into Book-to-Market (BE/ME, book value of equity/market value of equity) quintiles. Our sample includes 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 five fund trades. For each stock/date, we define BUYPROPORTION as the dollar value for buying in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. We put observations with BUYPROPORTION = 0 into the *AllSell* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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 the 1% level, ** for the 5% level, and * for the 10% level.

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.

(v) Sorting on Momentum and Buy Proportion

The next double-sorting 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 groups 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. We then place each stock into one of the five groups based on its past return.

Table 5 displays the returns of the 25 groups. The U-shaped pattern emerges across all five momentum quintiles. All of the differences between the *Disagree* and *AllBuy* and

Table 5
Momentum and Opinion Group Returns

	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	−14.25%	2.17%	8.99%	12.68%	11.60%
Disagree	−13.20%	−0.16%	7.09%	12.36%	12.73%
MinSell	−14.16%	1.73%	7.76%	12.01%	12.53%
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	10.99%	4.11%	8.27%	8.30%	2.45%
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.007)***
AllSell – Disagree	8.12%	13.19%	3.57%	13.21%	6.69%
	(0.010)**	(0.000)***	(0.014)**	(0.000)***	(0.000)***

Notes:
This table presents equal-weighted 6-month group returns for five opinion groups, sorted into Momentum (MOM) quintiles. MOM is the return from 12 months ago to one month ago. Our sample includes 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 five fund trades. For each stock/date, we define BUYPROPORTION as the dollar value for buying in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. We put observations with BUYPROPORTION = 0 into the *AllSell* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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 the 1% level, ** for the 5% level, and * for the 10% level.

Disagree and *AllSell* groups are large and 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* groups had significantly higher returns than did the *AllBuy* groups.

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 low future 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. We first define a buy (sell) proportion measure as the dollar value for buying (selling) in that stock on that day divided by the total dollar value for buying and selling in that stock on that day. DIVERGENCE is then defined as the minimum of the buy proportion and sell proportion measures. DIVERGENCE always takes on a value that is between 0 and 0.5. If all the trading is either buying or selling, DIVERGENCE will be equal to 0 (no divergence). If exactly half of the dollar trading value is buying and half is selling, DIVERGENCE will be equal to 0.5 (maximum divergence). For example, if there are $7 million buying and $3 million selling in Microsoft on one day, then the buy proportion will be 0.7 and sell proportion will be 0.3. Therefore, Microsoft 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 three interaction variables into our regressions. What drives the opinion divergence – low return relationships are short sale constraints. Miller's (1977) hypothesis 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), share price, and market value of equity. 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, e.g., Dechow et al., 2001; and D'Avolio, 2002). Stocks with low share prices and smaller market values tend to have lower liquidity. There is also empirical evidence that low price and small size stocks can deter arbitrageurs (see, e.g., Pontiff, 1996). Our interaction variables are DIVERGENCE_INSTHLDS, DIVERGENCE_PRC, and DIVERGENCE_LN(ME). DIVERGENCE_INSTHLDS is calculated as DIVERGENCE * (1 – institutional holdings), DIVERGENCE_PRC is calculated as DIVERGENCE * (1/price), and DIVERGENCE_LN(ME) is calculated as DIVERGENCE * (1/LN(ME)).

(i) Correlation Matrix

Table 6 reinforces our basic beliefs about the relationship between the independent variables and future returns. All four opinion divergence measures are negatively correlated with future returns. Consistent with other studies, MOM and LN(BE/ME) are positively correlated with future returns, while LN(ME) is negatively correlated with future returns. We also see that DIVERGENCE, DIVERGENCE_INSTHLDS, DIVERGENCE_PRC, and DIVERGENCE_LN(ME) are all highly correlated with one another. DIVERGENCE has a correlation with DIVERGENCE_INSTHLDS of 0.81, a correlation with DIVERGENCE_PRC of 0.73, and a correlation with DIVERGENCE_LN(ME) of 0.88. The three interaction terms, DIVERGENCE_INSTHLDS, DIVERGENCE_PRC, and DIVERGENCE_LN(ME) are also highly correlated with one another. To avoid any potential problems due to multicollinearity, we will not use these four variables in the same regression. Our BUYPROPORTION measure is calculated similarly as in the previous sections.

Table 6
Correlation Matrix

	6 Month Market-Adjusted Return	*LN(ME)*	*LN(BE/ME)*	*MOM*	*BUYPROPORTION*	*DIVERGENCE*	*DIVERGENCE_INSTHLDS*	*DIVERGENCE_PRC*
LN(ME)	−0.18							
LN(BE/ME)	0.15	−0.30						
MOM	0.20	−0.15	−0.08					
BUYPROPORTION	0.01	−0.04	−0.02	0.03				
DIVERGENCE	−0.05	0.16	−0.07	−0.04	−0.10			
DIVERGENCE_INSTHLDS	−0.09	0.21	−0.04	−0.06	−0.08	0.81		
DIVERGENCE_PRC	−0.05	−0.10	0.14	−0.12	−0.07	0.73	0.62	
DIVERGENCE_LN(ME)	−0.04	0.10	−0.05	−0.03	−0.10	0.88	0.80	0.75

Notes:
This table presents the correlation matrix of different variables. Our sample includes 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 months ago to 1 month ago. The unit of observation is stock/date. We exclude observations with less than five fund trades. For each stock/date, we define BUYPROPORTION (SELLPROPORTION) as the dollar value for buying (selling) in that stock on that day divided by the total dollar value for buying and selling in 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). DIVERGENCE_LN(ME) is defined as DIVERGENCE * (1/ln(ME)).

(ii) Regressions Tests

Table 7 shows the results of our regression tests. The dependent variable in all of the regressions is six-month market adjusted 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 future returns. These findings are consistent with previous univariate results.

In Regressions 5 and 6 we control for size, book-to-market, and momentum and find that DIVERGENCE coefficient is still negative and significant. In Regressions 7, 8 and 9, where we interact DIVERGENCE with short sale constraints proxies, the divergence measures are also significantly negative. 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 (0.000) is much smaller than the *p*-value for DIVERGENCE in Regression 5 (0.059). The magnitudes of the coefficients are not directly comparable. Regression 7 confirms our hypothesis 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 (0.001) is much smaller than is the *p*-value for DIVERGENCE Regression 5 (0.059). This again implies that the effect of opinion divergence on returns is stronger for stocks that have low stock prices, i.e. stocks that are harder to short. The results in Regression 9 are similar, though less significant statistically. These results are consistent with those in Boehme et al. (2006), 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 ANALYSIS

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

(i) Intra-Family Group 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 use the same group boundaries as we did in Section 3.

Table 8 reports the frequency and characteristics of the stocks in each of the different opinion groups. The first two columns in Table 8 report the number and percentage of observations that fall into each of the five opinion groups. 11.7% of the observations fall into the *Disagree* group versus 22.5% in Table 1 when we measured across the whole sample. Not surprisingly, managers who work at the same fund family and presumably share some common information tend to agree more, although there is still a fair amount of disagreement intra-family.

Similar to previous results, it is more common for the managers in our sample to buy in unison than it is for them to sell in unison. The *AllBuy* group makes up 33.4% of the sample, while the *AllSell* group makes up 22.9% of the sample. These group

Table 7
Regression Analysis

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Constant	0.049	0.068	0.066	0.602	0.596	0.596	0.569	0.643	0.601
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LN(ME)				−0.022	−0.022	−0.022	−0.020	−0.023	−0.022
				(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
LN(BE/ME)				0.051	0.051	0.051	0.051	0.053	0.051
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
MOM				0.124	0.124	0.124	0.123	0.119	0.124
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
BUYPROPORTION	0.006		0.002	0.001		−0.001			
	(0.598)		(0.864)	(0.946)		(0.958)			
DIVERGENCE		−0.104	−0.104		−0.035	−0.035			
		(0.000)***	(0.000)***		(0.059)*	(0.057)*			
DIVERGENCE_INSTHLDS							−0.227		
							(0.000)***		
DIVERGENCE_PRC								−2.280	
								(0.001)***	
DIVERGENCE_LN(ME)									−0.777
									(0.065)*
Adjusted R-squared	0.000	0.003	0.003	0.076	0.077	0.077	0.079	0.080	0.077

Notes:
This table presents regression results. Our sample includes 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 months ago to 1 month ago. The unit of observation is stock/date. We exclude observations with less than five fund trades. For each stock/date, we define BUYPROPORTION (SELLPROPORTION) as the dollar value for buying (selling) in that stock on that day divided by the total dollar value for buying and selling in 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). DIVERGENCE_LN(ME) is defined as DIVERGENCE * (1/ln(ME)). 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 the 1% level, ** for the 5% level, and * for the 10% level.

Table 8
Intra-Family Opinion Group Frequencies and Characteristics

	N	*% of N*	*ME ($M)*	*BE/ME*	*MOM*
AllSell	5,020	22.9%	14,589	0.50	−0.19%
MinBuy	3,797	17.3%	48,792	0.39	−6.03%
Disagree	2,570	11.7%	39,263	0.42	−3.96%
MinSell	3,195	14.6%	49,079	0.38	−4.48%
AllBuy	7,324	33.4%	17,456	0.45	3.65%
	21,906		29,401	0.44	−0.99%
Total	21,906		29,401	0.44	−0.99%

Notes:
This table presents opinion group frequencies and characteristics for five intra-family opinion groups. Our sample includes 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 five opinion groups are reported. Group 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 months ago to 1 month ago). The unit of observation is fund family/stock/date. We exclude observations with less than five fund trades. For each fund family/stock/date, we define BUYPROPORTION as the dollar value for buying within that fund family in that stock on that day divided by the total dollar value for buying and selling within that fund family in that stock on that day. We put observations with BUYPROPORTION = 0 into the *AllSell* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group.

frequencies are plotted in Figure, 3, Panel A. The next 3 columns in Table 8 report the characteristics of the stocks in the different groups.

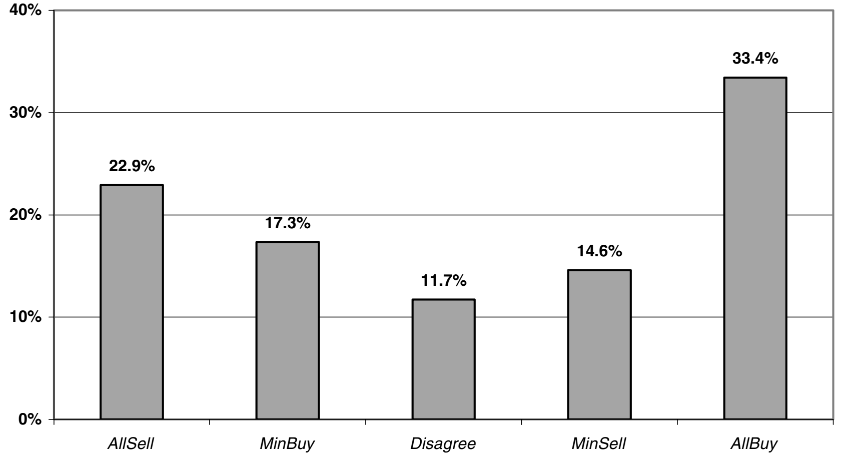
(ii) Intra-Family Group Returns Over Different Horizons

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

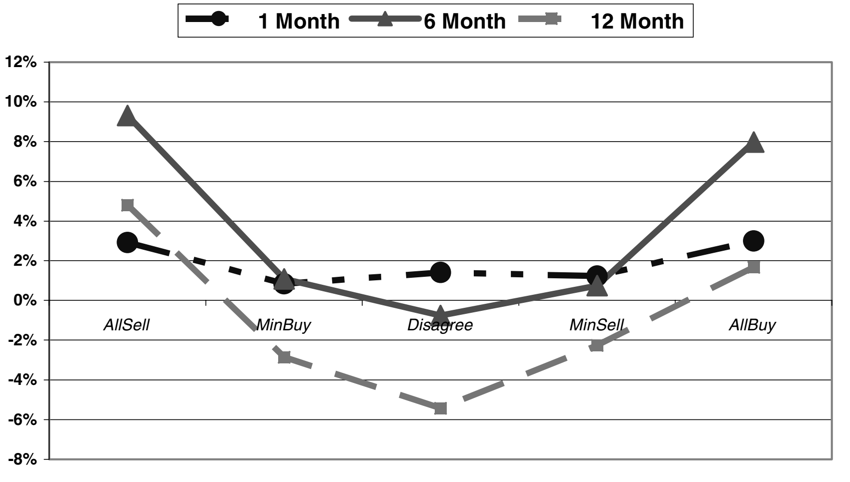
Table 9 shows that the *Disagree* group has low future returns. The differences between the *Disagree* group's returns and the *AllBuy* group's returns are 1.60%, 8.75% and 7.10% over 1, 6 and 12-month horizons. All of the differences are statistically significant. The differences between the *Disagree* group's returns and the *AllSell* group's returns are 1.52%, 10.09% and 10.24% over 1, 6 and 12-month horizons. All of the differences are also statistically significant. These results are similar to those reported in Table 2. This pattern implies that high divergence in opinion predicts low future returns, 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 3, Panel B. As in Table 2, Table 9 provides no evidence of managers possessing private information.

Figure 3

Panel A. Intra-Family Opinion Group Frequencies



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



Notes:
Panel A of this figure plots frequencies of five intra-family opinion groups, as reported in Table 8. Panel B of this figure plots equal-weighted group returns over 1, 6 and 12-month horizons for five intra-family opinion groups, as reported in Table 9. Our sample includes 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* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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.

Table 9
Intra-Family Opinion Group Returns Over Different Horizons

	1 Month	*6 Month*	*12 Month*
AllSell	2.92%	9.32%	4.81%
MinBuy	0.83%	1.08%	−2.87%
Disagree	1.40%	−0.76%	−5.43%
MinSell	1.23%	0.74%	−2.27%
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	1.60%	8.75%	7.10%
	(0.045)**	(0.000)***	(0.000)***
AllSell – Disagree	1.52%	10.09%	10.24%
	(0.004)***	(0.000)***	(0.000)***

Notes:
This table presents equal-weighted group returns over 1, 6 and 12-month horizons for five intra-family opinion groups. Our sample includes 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 five fund trades. For each fund family/stock/date, we define BUYPROPORTION as the dollar value for buying within that fund family in that stock on that day divided by the total dollar value for buying and selling within that fund family in 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* group, observations with 0 < BUYPROPORTION < = 0.3 into the *MinBuy* (Minority Buying) group, observations with 0.3 < BUYPROPORTION < = 0.7 into the *Disagree* group, observations with 0.7 < BUYPROPORTION < 1 into the *MinSell* group, and finally observations with BUYPROPORTION = 1 into the *AllBuy* group. 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 the 1% level, ** for the 5% level, and * for the 10% level.

(iii) Intra-Family Regression Tests

Similar to Section 4, the measure of disagreement in this section, DIVERGENCE, is constructed as a continuous variable. We first define a buy (sell) proportion measure as the dollar value for buying (selling) within that fund family in that stock on that day divided by the total dollar value for buying and selling within that fund family in that stock on that day. DIVERGENCE is then defined as the minimum of the buy proportion and sell proportion measures. Again, DIVERGENCE always takes on a value that is between 0 and 0.5. To avoid using repeated observations in our regressions we use an average of our intra-family DIVERGENCE measure for stocks' with multiple observations on the same day.

(a) Intra-Family Correlation Matrix

The correlation matrix in Table 10 reinforces our previous results with respect to the relationship between opinion divergence and future returns. All four of the divergence measures are negatively correlated with future returns. We also see that DIVERGENCE, DIVERGENCE_INSTHLDS, DIVERGENCE_PRC, and DIVERGENCE_LN(ME) are all highly correlated with one another. DIVERGENCE has a correlation with DIVERGENCE_INSTHLDS of 0.87, a correlation with DIVERGENCE_PRC of 0.78, and a correlation with DIVERGENCE_LN(ME) of 0.90. The three interaction terms, DIVERGENCE_INSTHLDS, DIVERGENCE_PRC, and DIVERGENCE_LN(ME) are also highly correlated with one another. To avoid any potential problems due to multicollinearity, we will not use these four variables in the same regression.

(b) Intra-Family Regressions

The Regressions in Table 11 are similar to those in Table 7, only the DIVERGENCE measures in Table 11 is constructed at the family level, while the DIVERGENCE measure in Table 7 is constructed within the entire sample. The signs for all of the DIVERGENCE coefficients are either significantly negative or not significantly different from zero. 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 effect on the returns of stocks that are more difficult to short. 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. Compared to the results in Table 7, the results in Table 11 are weaker overall, especially for regressions 5, 6 and 9. This may be partially due to the fact that we have a smaller number of observations for these intra-family results than for previous results across the whole sample.

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 managers on average do not possess such private 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 managers 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 hypothesis 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 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.

Table 10

Intra-Family Correlation Matrix

	6 Month Market-Adjusted Return	*LN(ME)*	*LN(BE/ME)*	*MOM*	*BUYPROPORTION*	*DIVERGENCE*	*DIVERGENCE_INSTHLDS*	*DIVERGENCE_DIVERGENCE*
LN(ME)	−0.22							
LN(BE/ME)	0.16	−0.34						
MOM	0.19	−0.18	−0.07					
BUYPROPORTION	0.00	−0.04	−0.04	0.04				
DIVERGENCE	−0.03	0.14	−0.04	−0.03	−0.06			
DIVERGENCE_INSTHLDS	−0.06	0.16	−0.03	−0.05	−0.05	0.87		
DIVERGENCE_PRC	−0.02	−0.05	0.11	−0.07	−0.04	0.78	0.71	
DIVERGENCE_LN(ME)	−0.02	0.09	−0.02	−0.03	−0.05	0.90	0.86	0.80

Notes:
This table presents the correlation matrix of different variables at the intra-family level. Our sample includes 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 months ago to one month ago. The initial unit of observation is fund family/stock/date. We exclude observations with less than five fund trades. For each fund family/stock/date, we define BUYPROPORTION (SELLROPORTION) as the dollar value for buying (selling) within that fund family in that stock on that day divided by the total dollar value for buying and selling within that fund family in 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). DIVERGENCE_LN(ME) is defined as DIVERGENCE * (1/ln(ME)).

Table 11

Intra-Family Regression Analysis

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Constant	0.051	0.056	0.057	0.722	0.716	0.722	0.702	0.725	0.716
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LN(ME)				−0.028	−0.027	−0.028	−0.027	−0.028	−0.028
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
LN(BE/ME)				0.046	0.047	0.046	0.047	0.048	0.047
				(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.002)***	(0.003)***
MOM				0.108	0.108	0.108	0.108	0.106	0.108
				(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
BUYPROPORTION	−0.001		−0.002	−0.008		−0.008			
	(0.951)		(0.882)	(0.572)		(0.572)			
DIVERGENCE		−0.073	−0.073		0.000	−0.001			
		(0.045)**	(0.044)**		(0.994)	(0.976)			
DIVERGENCE_INSTHLDS							−0.153		
							(0.055)*		
DIVERGENCE_PRC								−1.411	
								(0.131)	
DIVERGENCE_LN(ME)									0.072
									(0.926)
Adjusted *R*-squared	−0.000	0.001	0.001	0.082	0.081	0.081	0.082	0.082	0.081

Notes:
This table presents intra-family regression results. Our sample includes 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 months ago to one month ago. The initial unit of observation is fund family/stock/date. We exclude observations with less than five fund trades. For each fund family/stock/date, we define BUYPROPORTION (SELLROPORTION) as the dollar value for buying (selling) within that fund family in that stock on that day divided by the total dollar value for buying and selling within that fund family in 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). DIVERGENCE_LN(ME) is defined as DIVERGENCE * (1/ln(ME)). 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 the 1% level, ** for the 5% level, and * for the 10% level.

In terms of future extensions, there are two potentially fruitful directions. First, it might be interesting to study the determinants of opinion divergence. Intuitively, information events may trigger opinion divergence. Comparisons between opinion divergence triggered by information events versus opinion divergence not triggered by information events may yield further insights. Second, it might also be interesting to examine the dynamics of opinion divergence, such as the persistence and evolution of opinion divergence in individual stocks over time.

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