Three essays on empirical asset pricing

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ASSET PRICING**

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2012

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Introduction

The dissertation comprises three essays on empirical asset pricing. The essays connect to one another as the corporate earnings announcement event is the key to constructing the main variables in the three studies.

Essay 1 examines relative profitability of stock recommendations associated with analyst pessimism. Analysts are by definition pessimistic if their prior earnings forecasts tend to fall below consensus. We find that recommendations or revisions are more profitable when pessimistic rather than optimistic analysts issue them in the U.S. from 1994 to 2009. The return differential is around 4.20 percent per year for the stock recommendation, and 7.08 percent for the recommendation revision (to buy or strong buy), between the top and bottom pessimism tercile of analysts. Our finding does not result from the conditional pessimism measure of Hugon and Muslu (2010) or another ex-ante measure of earnings forecast accuracy.

Essay 2 studies stock estimation risk and its implication on the cross section of stock returns. When prior information is of low quality, price change is often large on the earnings announcement date. We use the standard deviation of historical earnings announcement return as a proxy for stock estimation risk. We find that there is no significant premium to estimation risk in the U.S. stock market from 1978 to 2009, a result at odd with the theoretical prediction of Kumar, Sorescu, Boehmer and Danielsen (2008). In addition, we find that price and earnings momentum as well as forecast-revision drift is stronger among stocks with higher estimation risk, a result consistent with the notion that investors suffer from bias in processing information.

Essay 3 follows on the literature's extensive use of earnings announcement effects to show informed trading of financial institutions. In this study, we use a measure of investment skills or informational superiority for mutual funds based on their buy trades. If a mutual fund buys into stocks that subsequently enjoy high earnings announcement returns, the fund is either skilled or informed according to this measure. From 1984 to 2009, this measure successfully predicts fund winners. The top performing decile of mutual funds beat the bottom by around 50 basis points per quarter. The measure shows persistence over time. We infer that the inherent investment talent or informational advantage of fund managers contributes to alpha.

Contents

Acknowledgements	3
Introduction.....	4
Essay One: Do Pessimistic Analysts Issue More Profitable Stock Recommendations?.....	9
I. Introduction.....	10
II. Research Design and Hypothesis Development.....	14
II.1 The measure of pessimism for security analysts.....	14
Figure 1: Distance of Analyst Forecast away from Consensus.....	15
II.2 Hypothesis development	17
III. Sample formation.....	19
IV. Empirical Analysis.....	21
IV.1 Calendar portfolio approach of Barber, Lehavy, McNichols, and Trueman (2001).....	22
IV.2 Calendar portfolio approach of Fang and Yasuda (2011)	24
IV.3 Regression approach of Jegadeesh, Kim, Krische and Lee (2004).....	26
IV.4 Regression approach of George and Hwang (2010)	28
IV.5 Discussion of the conditional pessimistic measure of Hugon and Muslu (2010)	31
IV.6 Discussion of ex-ante forecast accuracy and recommendation profitability.....	32
V. Conclusion	33
Reference	35
Appendix A: Variable List.....	37
Table 1: Sample Selection.....	38
Table 2: Descriptive statistics	39
Table 3: Calendar portfolio approach of Barber et al. (2001).....	41
Table 4: Calendar portfolio approach of Fang and Yasuda (2011).....	43
Table 5: Regression approach of Jegadeesh et al. (2004)	45
Table 6: The <i>J-K</i> regression approach of George and Hwang (2010).....	47
Table 7: The analyst pessimism measure of Hugon and Muslu (2010)	51
Table 8: Ex-ante forecast accuracy and subsequent profitability of stock recommendations.....	53
Figure 2: Cumulative abnormal return from day -1 to day 20 around the revision date.....	54
Essay Two: Estimation Risk, Stock Returns and Momentum	56
I. Introduction.....	57
II. Research Design.....	59
IV.1 A simple model	60

Figure 1: Time line for a simple model illustrating estimation risk	60
IV.2 Estimation risk proxy	62
Figure 2: Time line in constructing our proxy for estimation risk	63
IV.3 Hypothesis development	63
III. Sample formation	67
IV. Empirical Results	71
IV.1 Pricing of estimation risk	71
IV.2 Momentum and estimation risk.....	76
IV.3 Reversal indication.....	79
IV.4 Robustness tests	80
V. Conclusion	82
Reference	84
Appendix A: Variable definition and computation/source	87
Table 1: Summary Statistics	89
Table 2: Average returns to DEAR portfolios	90
Table 3: Fama-Macbeth regression of monthly stock returns.....	93
Table 4: Differential momentum and drift effect -- sort evidence	94
Table 5: Differential momentum and drift effect -- regression evidence.....	96
Table 6: Reversal indication.....	98
Table 7: Robustness tests	100
Essay Three: Informed Trading and Mutual Fund Alpha	103
I. Introduction.....	104
II. Sample formation.....	109
III. Empirical Design.....	112
III.1 The measure of the investment skills or information superiority of mutual funds	112
Figure 1: Time line for defining the measure.....	113
III.2 Fund performance measures	115
III.3 Fund flow and other control variables.....	117
IV. Empirical Analysis	120
IV.1 Regression analysis	120
IV.2 Portfolio analysis.....	122
IV.3 Persistence of the measure	123
IV.4 Decomposition of buys into first buys and non-first buys	126

IV.5	Characteristics-based measures of fund performance	127
IV.6	Return predictability when a post-earnings announcement drift factor is introduced.....	129
IV.7	The effect of investment styles on the return predictability	130
IV.8	Sub-period analysis	133
IV.9	Stock performance evidence	134
IV.10	Analysis using the monthly file.....	135
IV.11	Simulated mutual funds.....	136
IV.12	Comparison with other measures of fund skills	137
V.	Conclusion	139
	Reference	141
	Table 1: Summary Statistics	144
	Table 2: Fama-MacBeth regression of quarterly fund returns	145
	Table 3: Return to quarterly fund portfolios sorted by the measure	147
	Table 4: Persistence of the measure: The measure level in the subsequent four quarters.....	148
	Table 5: Persistence of the measure: Regression evidence	149
	Table 6: Decomposition of buys into first buys and non-first buys	151
	Table 7: Characteristics-based measure of fund return.....	152
	Table 8: Return predictability when an earnings drift factor is introduced.....	155
	Table 9: The effect of mutual fund style on the return predictability of the measure	156
	Table 10: Sub-period analysis	158
	Table 11: Stock performance evidence	159
	Table 12: Unconditional alphas from monthly portfolios	161
	Table 13: Simulated mutual funds	162
	Table 14: Comparison with other measures of fund skills.....	163
	Figure 2: Persistence of the measure: Average decile ranks of <i>CAR1_BUY</i> in the surrounding 8 quarters.....	164
	Appendix A: Monthly stock portfolios sorted by <i>EAR</i>	165

Essay One: Do Pessimistic Analysts Issue More Profitable Stock Recommendations?

Abstract

This study examines relative profitability of stock recommendations associated with analyst pessimism. Analysts are pessimistic if their prior earnings forecast tend to fall below consensus. We find that recommendations or revisions are more profitable when pessimistic rather than optimistic analysts issue them in the U.S. from 1994 to 2009. The return differential is around 4.20 percent per year for the stock recommendation, and 7.08 percent for the recommendation revision (to buy or strong buy) between the top and bottom pessimism tercile of analysts. Our finding does not result from the conditional pessimism measure of Hugon and Muslu (2010) or another ex-ante measure of earnings forecast accuracy.

Keywords: security analysts, pessimism, stock recommendations, institutional investors

JEL: G14 G24 M4

I. Introduction

Can security analysts who are restrained in their earnings forecasts also be misunderstood by the market? When those analysts issue supposedly unequivocal buy and sell recommendations, will their voices go unnoticed and have strong return predictability afterwards? Hugon and Muslu (2010) point to future studies to uncover the relationship between analyst pessimism and stock recommendations. Our study responds to this call.

We are different from Hugon and Muslu (2010) in defining pessimism for security analysts, whose approach is motivated by the widely used accounting pessimism measure of Basu (1997). According to Hugon and Muslu (2010), if analysts are more responsive to bad news relative to their peers, they are pessimistic. Such a pessimism measure is conditional (based on reaction to bad news) and relative (compared with peers). Jiang, Kumar and Law (2011) posit that the pessimism measure of Hugon and Muslu (2010) bear little correlation with their measure of analyst pessimism, whether analysts belong to the pessimistic Republican Party in the U.S.

In this study, we explore another notion of pessimism. We measure pessimism for security analysts based on their earnings forecast behaviors before the earnings announcement date. Analysts are regarded as pessimistic if they tend to predict earnings below consensus. The mindset of pessimistic analysts is like that of accountants, who transcends the pessimism of the proverb, ‘Do not count your chicken before they are hatched,’ saying, ‘Here are a lot of chickens already safely hatched, but for the love of Mike, use discretion and don’t count them all, for perhaps some will die.’ (Hatfield, 1927).

We retrieve analysts’ relative positions of earnings forecasts before the earnings announcement date. This approach helps address two concerns. One, there is no ex-post information involved and the measure is an ex-ante one. Two, we avoid distorted incentives causing analysts to walk down the earnings estimates (e.g., Kang, O’Brien, and Sivaramakrishnan, 1994; Lim, 2001). As

forecasted earnings are announced on the next day, analysts are more likely to produce their genuine estimates and reveal their type to the extent that they care about their reputations in the security analysis business.

Should pessimistic analysts who are cautious about future earnings issue recommendations that are more profitable? We identify two channels through which pessimistic analysts might do so. First, pessimistic analysts are able to unwind the general bias towards optimism in analysts' earnings forecasts. Some pessimistic analysts even receive private information from managers as suggested by Ke and Yu (2006). Second, pessimistic analysts do not face distorted incentives as optimistic analysts do. Those who are optimistic may have rationally been optimistic in earnings forecast in the face of distorted incentives (see, for example, Hugon and Muslu (2010)). The stock recommendation is another tool of their decision. Pessimistic analysts without the harm of bad incentives can produce more objective and better stock recommendations.

With a measure of analyst pessimism, we examine whether pessimistic analysts produce stock recommendations that are more profitable. We test on almost the largest recommendation dataset from 1994 to 2009 in the U.S.¹ We divide the population of analysts into three groups (*pessimistic*, *neutral* and *optimistic*) or quintiles at the end of each quarter. We then trace the performance of stocks they cover and examine the profitability of their stock recommendations or recommendation revisions in the subsequent quarter. We use two daily calendar-time portfolio formation techniques and two multivariate regression frameworks in our tests. Results of the four approaches paint the following picture: Pessimistic analysts generate stock recommendations or recommendation revisions that are more profitable than optimistic analysts do.

By the daily calendar-time portfolio approach of Barber, Lehavy, McNichols, and Trueman (2001), we find that stocks that pessimistic analysts recommend to buy outperform and stocks they recommend to sell underperform. The return differential between pessimistic and optimistic

¹See a similar argument in Fang and Yasuda (2011).

analysts for the buy and sell stocks is 22 basis points per month and 13 basis points per month, respectively. Therefore, a hedge portfolio based on the recommendations of pessimistic analysts produces 35 basis points per month more return than the hedge portfolio based on the recommendations of optimistic analysts. In other words, the value of stock recommendation of pessimistic analysts' exceeds that of optimistic analysts by 4.2% per year.

By the daily calendar-time portfolio approach of Fang and Yasuda (2011), we find that the recommendation just recently revised to buy or strong buy (I/B/E/S rating = 1 or 2) is much more profitable when it comes from pessimistic analysts rather than optimistic analysts. The return differential between pessimistic analysts and optimistic analysts (in terciles) is 59 basis points per month, an equivalent of 7.08 percent per year.² Also notable in this part of analysis is that the analyst type lagged by four quarters (one year) still produces differential profitability in recommendation revisions, suggesting that pessimism may exist in the cross section of analysts as a persistent trait.

We proceed to the multivariate framework of Jegadeesh, Kim, Krische and Lee (2004). We confirm their major conclusion that the change in consensus recommendation is much more informative about future stock returns than the consensus recommendation itself. Dividing the regression sample into pessimistic-, neutral- and optimistic-analyst sub-samples, we find that the consensus recommendation or the change in consensus recommendation is much informative in the pessimistic-analyst sub-sample than in the optimistic-analyst sub-sample. The results suggest that stock recommendations or recommendation revisions coming from pessimistic analysts are more informative than those from optimistic analysts are. It is also noteworthy that the analyst type lagged by four quarters and eight quarters still show that pessimistic analysts issue more profitable stock recommendations.

²This number is comparable to Fang and Yasuda (2011) who report that star analysts' recommendations are more profitable than non-star analysts by 7 percent per year.

The final framework of analysis is the calendar-time regression approach of George and Hwang (2010). This approach is arguably better at capturing the sole effect of the variables of interest. In addition, the regression results immediately relates to implemental investment strategies and concrete calendar portfolios. Under this approach, we find that the buy recommendations of pessimistic analysts are more profitable than that of optimistic analysts. The hedge portfolio according to the average recommendation level within pessimistic analysts is 2.64 percent larger than that within optimistic analysts if the holding period is 12 months. The hedge portfolio according to the change in the average recommendation level within pessimistic analysts is 6.6 percent larger than that within optimistic analysts if the holding period is 12 months.

We then examine if our result is driven by the conditional pessimism measure of Hugon and Muslu (2010) or another ex-ante measure of earnings forecast accuracy. We do not find that the analyst pessimism measure of Hugon and Muslu (2010) produces differential profitability of stock recommendations. Another measure of prior earnings forecast accuracy also fails to produce the effects we have documented.

Our study connects to the literature in three ways. First, we measure analyst pessimism on the analysts' earnings forecasting behaviors before the earnings announcement date. Hugon and Muslu (2010) posit that stock market calls for pessimistic analysts in that the market response to their earnings forecast revision is large, especially when there is large institutional ownership. Jiang et al. (2011) show that analysts issue more accurate and bold earnings forecast when their political values are pessimistic.

Second, our study relates to studies that associate the analyst earnings forecast behaviors with stock recommendations. Loh and Mian (2006) claim that the number of such studies is still limited and they find a contemporaneous relationship between earnings forecast accuracy and profitability of stock recommendations. Bradshaw (2004) maps the earnings forecasts to stock recommendations and find most analysts use heuristic models rather than present value models to

reach recommendation opinions. Eames, Glover and Kennedy (2002) find that the buy and sell recommendation predicts optimism and pessimism in earnings forecasts, respectively.

Last, our study relates to those studies on the profitability of stock recommendations. Studies generally suggest that analysts produce valuable recommendations to the investors. Representative work includes Elton, Gruber, and Grossman (1986), Womack (1996), Barber et al. (2001), Jegadeesh et al. (2004), Bagnoli, Clement, Crawley and Watts (2009), Fang and Yasuda (2011). Our work asserts that analyst pessimism may be useful to investors in distinguishing good recommendations from bad ones.

We organize the rest of the paper as follows. Section II introduces our new measure of pessimism for security analysts and develops the sole testable hypothesis regarding pessimistic analysts. Section III describes our sample. Section IV presents empirical results. Section V concludes.

II. Research Design and Hypothesis Development

In this section, we describe the measure of pessimism for security analysts, which is based on their earnings forecast behaviors. We then develop the sole testable hypothesis in our study: Pessimistic analysts issue stock recommendations that are more profitable.

II.1 The measure of pessimism for security analysts

The measure of pessimism for security analysts stems from the straightforward idea that pessimistic analysts are not overly optimistic. Analysts tend to emphasize good news and downplay bad news (Easterwood and Nutt, 1999), and are more likely to issue optimistic forecasts (see, e.g., Irvine, 2004; Jackson, 2005; Cowen, Groysberg, and Healy, 2006). It is yet clear that analysts act pessimistically in an absolute sense (Hugon and Muslu, 2010). However, to the extent that pessimism mitigates the over-optimistic bias well documented in the analyst literature, we conjecture that their earnings forecasts tend to fall below consensus. The average earnings forecast

would be higher without their participation. If analysts consistently forecast earnings lower than the average, they are by our definition pessimistic.³

We choose the date right before the earnings announcement date and examine the distribution of earnings forecasts made by analysts.⁴ The corporate earnings are announced on the next day. This avoids the well known earnings forecast problem of “walking down”.⁵ On this date, we obtain all the prevailing earnings forecasts by analysts. The consensus earnings forecast is the mean forecast of all analysts. The distance of earnings forecast by an individual analyst away from the consensus is the difference between her forecast and the mean forecast scaled by the standard deviation of all forecasts.⁶ Figure 1 illustrates the idea.

Figure 1: Distance of Analyst Forecast away from Consensus

We define the distance of analyst i 's forecast away from consensus for her forecast of earnings of stock j to be announced on date t as

$$(1) \quad DIST_{i,j,t} = (frcst_{i,j,t} - \frac{1}{N_i} \sum_{j=1}^{N_i} frcst_{i,j,t}) / std(frcst_{i,t}),$$

³This notion of pessimism is also discussed as a pessimism measure in Hugon and Muslu (2010). Our originality lies in using the announcement window to examine analyst forecasts and determine the measure of analyst pessimism.

⁴The quarterly earnings forecasts are as just important as annual earnings forecast in our research setting.

⁵ Kang, O'Brien, and Sivaramakrishnan (1994) and Lim (2001) that analysts walk down their estimates as the forecast date approaches the earnings announcement date.

⁶We also try it to scale by the preceding month's stock price. The results are qualitatively similar.

where $frcst_{i,j,t}$ is analyst i 's forecast of earnings of stock j to be announced on date t ; N_i is the number of analysts who are engaged in forecasting earnings of stock i to be announced on date t ; $std(frcst_{i,t})$ is the standard deviation of all forecasts of earnings of stock i to be announced on date t .

Pessimistic analysts are cautious about future realization of earnings. They tend to make forecasts below the average, and their distance away from consensus is negative. To capture the idea, we average the distance across all the stocks that one analyst cover in a quarter to obtain the measure of pessimism for this analyst-quarter, denoted as

$$(2) \quad avgDIST_{i,T} = \frac{1}{K_{i,T}} \sum_{j=1}^{K_{i,T}} DIST_{i,j,t},$$

where $DIST_{i,j,t}$ is the distance of analyst i 's forecast away from consensus for her forecast of earnings of stock i to be announced on a certain date during quarter T ; $K_{i,T}$ is the number of stocks that are covered by analyst i in this quarter.⁷ We sort the population of analysts in each quarter into deciles with this variable and obtain its quarterly decile rank, $DavgDIST_{j,T}$.

At the beginning of each quarter Q , we use the average of $DavgDIST_{j,T}$ in the past four quarters ($Q-4$: $Q-1$, current quarter exclusive) to compute the pessimism measure for analyst j ,

$$(3) \quad Pessi_{j,Q} = \frac{1}{4} \sum_{T=Q-4}^{Q-1} DavgDIST_{j,T}.^8$$

In most analysis, we sort analysts by this measure into three groups, labeled as *pessimistic*, *neutral* and *optimistic*. We also sort them into quintiles in other analysis. We analyze the subsequent

⁷We require $K_{i,T}$ to be equal or greater than 3.

⁸We require that the pessimism measure for the analyst is not missing consecutively in the past four quarters. We find that the results are qualitatively similar when we do not impose the above two requirements under the two calendar-time portfolio approaches.

profitability of stock recommendations within different analyst groups. Therefore, the measure does not involve ex-post information and is an ex-ante measure of analyst pessimism.⁹

II.2 Hypothesis development

Earnings forecasts and stock recommendations are two activities pursued by the same individual. Givoly and Lakonishok (1984) contend that next to stock recommendations, earnings forecasts are perhaps the most notable output of financial analysts. Bradshaw (2004) maps analysts' earnings forecast to their stock recommendations. He finds that analysts make recommendations using heuristic PEG models rather than more scientific valuation models. Loh and Mian (2006) find a contemporaneous positive association between earnings forecast accuracy and stock recommendation profitability. Hall and Tacon (2010), on the other hand, find that analysts who made accurate earnings forecasts in the prior year or quarter do not necessarily make more profitable recommendations.

In this paper, we hypothesize that pessimistic analysts may produce more profitable stock recommendations. The first avenue for this to happen is that pessimistic analysts make better assessment of future earnings. There are two reasons for this claim. First, there exists the general optimism bias among analysts when it comes to earnings forecast (see, for example, Richardson, Teoh and Wysocki 2004). Pessimistic analysts are able to unwind such a bias. Second, the pessimistic analysts may receive private information from company managers. Ke and Yu (2006) hypothesize that the OP analysts who start with optimistic forecasts and ends with pessimistic and beatable forecasts please the managers. They show the OP analysts produce forecasts that are more accurate, and that they less likely lose jobs.

Better earnings forecasts lead to better stock recommendations because the two activities are processed by one brain. Eames, Glover, and Kennedy (2002) show that there exist positive

⁹The measure is also absolute in the sense that analysts pessimistic underestimate earnings irrespectively of earnings news, unlike in Hugon and Muslu (2010).

earnings forecast error for buy recommendations and negative forecast error for sell recommendations, supporting their “objectivity illusion hypothesis”, meaning, the unconscious tendency to process information in a manner that supports one’s goal. To the extent that pessimistic analysts make better forecasts of future earnings, their stock recommendations are likely to be more correct and more profitable.

The second avenue is that pessimistic analysts subjecting to less distorted incentives. Analysts may inflate earnings forecasts for the benefit of the company they work for, to boost stock trade and generate commission, to please the clients of the investment banking division of the same company. Optimistic analysts facing those distorted incentives might have rationally chosen to act optimistically (see, for example, Hugon and Muslu, 2010). They may use the stock recommendations as another convenient tool to play the optimistic strategy. Pessimistic analysts, less constrained by distorted incentives, can issue objective and profitable stock recommendations.

With the above analysis, we reach the sole testable hypothesis in the alternative form for our study:

Hypothesis: Stock recommendations or recommendation revisions issued by pessimistic security analysts are more profitable than those issued by optimistic analysts are.

The first order business of our study is to test the above hypothesis using all the available data in the U.S. security market. We leave it to future research to uncover the exact underlying channel why a positive association exists between analyst pessimism and profitability of stock recommendations.

III. Sample formation

We obtain analysts earnings forecasts and the actual earnings announcement dates from I/B/E/S detail file from 1993 to 2009 because I/B/E/S stock recommendations only start from 1994.¹⁰ Each stock needs to have at least three analysts to calculate the standard deviation of forecasts. Based on this sample, we compute our quarterly measure of analyst pessimism as in Eq. (3). As a result, we have quarterly measures of analyst pessimism, known at the beginning of each calendar quarter, for 7,236 unique analysts from 1994 to 2009.

We obtain analysts' recommendations from I/B/E/S detail recommendation file from 1994 to 2009, which is almost the entire series available from I/B/E/S (Fang and Yasuda, 2011). Different brokers have different rating systems. I/B/E/S converts them into a five-point rating system (1=strong buy, 2=buy, 3=held, 4=sell, 5=strong sell). In our analysis, we use the transformation of (3- I/B/E/S rating) so that higher ratings are signals to buy and lower ratings are signals to sell.

We will construct daily calendar-time portfolios similar to Barber et al. (2001), and Loh and Mian (2006). Therefore, we merge the analyst stock recommendations with daily stock returns from CRSP from 1994 to 2009. We require stocks to be greater than \$5 dollar (no penny stocks), to be common stocks (share code 1 or 2). We then further merge them with our quarterly measure of analyst pessimism. This procedure results in 5,872 unique analysts and 9,006 unique stocks in the daily calendar-time file from 1994 to 2009. With this file, the recommendation value of each analyst-stock obtains at the beginning of each trading day.

We will also use the regression framework of Jegadeesh et al. (2004). So we obtain stock monthly returns and other control variables as listed in Jegadeesh et al. (2004). The variables are winsorized at 0.5 percent at both ends in each month. Calculating these variables requires data from Compustat and I/B/E/S. The resulting common stocks are used to subset the daily calendar

¹⁰There is another benefit as prior studies (O'Brien, 1988; Zitzewitz, 2001; Bernhardt, Campello and Kutsoati, 2004) suggest that the earnings announcement dates are unreliable to some degree before 1993.

file as mentioned above, which in turn will be used in our regression analysis. We find there are 5,854 unique analysts and 7,797 unique stocks from 1994 to 2009.¹¹ Table 1 describes our sample selection process.

Table 1 is about here.

We proceed to characterize the measure of analyst pessimism, show the distribution of stock recommendations and recommendation revisions by analyst type, and provide descriptive statistics on the sample stocks covered by different groups of analysts. We sort analysts into three groups (*pessimistic*, *neutral* and *optimistic*). If the analyst classification is proper by the measure of pessimism, and pessimism as a personal trait is arguably persistent, we should see persistence of our analyst pessimism measure. Panel A provides the transition probability of analyst type over different horizons. The moving average of decile rank of *avgDIST* has been used to define the measure of analyst pessimism. The analyst type has to show strong persistence in one quarter's time as three other quarters overlapped in the definition of the pessimism measure. After four and eight quarters, however, there is no such a mechanical link. From Panel A, it is not surprising to see that over one-quarter's time, analyst type is persistent. It is interesting to find robust persistence after four and eight quarters, as around 50 percent of pessimistic analyst and 50 percent of optimistic analysts retain their original types. The Chi-square test results reject the null hypothesis across the board that the relative proportions of the subsequent analyst type (one-, four- and eight-quarters after) are independent of the prior type.

Table 2 is about here.

We obtain the prevailing recommendations at the end of last quarter issued by analysts. Panel B shows the well-known optimism bias in stock recommendations. The total number of sell and strong-sell recommendations only accounts for less than 8% of the population.¹² ¹³ More

¹¹The average number of analysts is 3098 from 1993 to 2009 in Fang and Yasuda (2011).

¹²Loh and Mian (2006) reports 5% for his sample from 1993 (October) to 1999.

importantly, Panel B does not show analysts of different types show much difference in recommendation behaviors. Pessimistic analysts do not necessarily issue more sell recommendations or less buy recommendations than optimistic analysts. Panel C shows the recommendation changes that have occurred in last quarter, if there are. There are 258, 310 recommendation revisions observed. Pessimistic analysts initiate more changes in terms of the number of revisions. However, relative to the total revisions made within each analyst group, unreported column percentages show that there is not much difference across different groups of analysts. Pessimistic analysts do not necessarily make a smaller or larger proportion of small changes than optimistic peers.

Panel D provides summary statistics on the regression sample stocks by different types of analysts that cover them. Appendix A provides definitions on these variables. We find that the number of stocks does not vary much across analyst type. The number of observations reported in this panel is slightly larger than that reported for the multivariate regression analysis of later section because the regressions require the variables to be jointly non-missing. There is not much difference in terms of firm characteristics except the accounting accruals. Optimistic analysts seem to be attracted to high accrual firms, 4.1 percent versus 3.28 percent for pessimistic analysts.

Overall, the analyst type seems to be persistent. There is not much difference in the recommendation activities across analyst type. The stocks they cover do not obviously differ. Therefore, it is likely that our empirical result does result from the analyst pessimism and not the other variables.

IV. Empirical Analysis

In this section, we use both the portfolio and regression approaches to show differential profitability of stock recommendations across different groups of analysts. The recommendation

¹³Rees, Sharpe and Twedt (2011) find that pessimistic recommendations attract more press attention, and this helps analysts' careers.

level as well as the recommendation change comes into analysis. We first sort analysts into three groups (*pessimistic*, *neutral* and *optimistic*) or quintiles. We follow each group of analysts, trace the stocks they issue recommendations on, and act on their recommendations. In this way, we draw inference on the relative profitability of recommendation associated with analyst pessimism. Overall, our results suggest that stock recommendations of pessimistic analysts are more valuable than those of optimistic analysts are.

IV.1 Calendar portfolio approach of Barber, Lehavy, McNichols, and Trueman (2001)

Following Barber et al. (2001) and Loh and Mian (2006), we construct calendar-time daily stock portfolios based on the daily average recommendation rating of each stock. This approach examines the value of the recommendation level to investors.¹⁴

The average recommendation rating for stock i on date t is the average of all ratings of analysts about this firm on date t , formally expressed as,

$$(4) \quad \bar{A}_{j,t} = \frac{1}{n_{j,t}} \sum_{i=1}^{n_{j,t}} A_{i,j,t-1},$$

where $A_{i,j,t-1}$ is analyst i 's outstanding recommendation rating of stock j on date $t-1$, $n_{j,t}$ is the number of analysts on date t .

Stocks are sorted into three distinct portfolios (*buy*, *hold* and *sell*) according to the average rating within each group of analysts of different pessimism.¹⁵ The stocks are equally weighted in the

¹⁴Unlike Loh and Mian (2006), the strategy here is implementable because we use the ex-ante measure of analyst pessimism. However, Barber et al. (2001) suggest that the daily re-balanced portfolio is very costly in terms of transaction costs. The results here are only to provide evidence that stock recommendations from pessimistic analysts are more profitable. The regression results in later sections likely turn into implemental and profitable strategies.

¹⁵We try the cut-off points to buy or sell stocks as in Loh and Mian (2006). The results are qualitatively similar. By not using the arbitrary cut-off points, we ensure that the number of stocks does not vary greatly across different portfolios.

portfolios.¹⁶ It is noteworthy that the average recommendation is obtained within each group of analysts. We do not pool together all the analysts' recommendations about the firm in the analyst universe. In addition, the firms may be different across the analyst groups because different analysts choose to cover different firms. At the same time, some firms repeat themselves as many analysts cover them simultaneously.

We follow from Barber et al. (2001) and Loh and Mian (2006) to compound daily portfolio returns into monthly returns. For each month in our sample period, the daily returns for each portfolio $R_{p,t}$ are compounded over the n trading days of the month to yield a month return, $R_{p,T}$:

$$(5) \quad R_{p,T} = \prod_{t=1}^n (1 + R_{p,t}).$$

We use monthly factor returns to evaluate return performance across portfolios. Specifically, we calculate the risk-adjusted returns using the Fama-French three-factor model, and the Carhart four-factor model as in the following models:

$$(6) \quad (R_{p,T} - r_{f,T}) = \alpha_p + b_p \cdot MKT_T + s_p \cdot SMB_T + h_p \cdot HML_T + \varepsilon_T,$$

$$(7) \quad (R_{p,T} - r_{f,T}) = \alpha_p + b_p \cdot MKT_T + s_p \cdot SMB_T + h_p \cdot HML_T + u_p \cdot UMD_T + \varepsilon_T.$$

where $(R_{p,T} - r_{f,T})$ is the portfolio excess return over risk-free interest rate in month T , and MKT_T , SMB_T , HML_T , and UMD_T are the monthly market, size, book-to-market and momentum factors, respectively.

Table 3 is about here.

Table 3 reports the average returns to the daily calendar-time portfolios (*buy*, *hold* and *sell*) within each group of analysts (*pessimistic*, *neutral* and *optimistic*). In Panel A of Table 3, it is easy to see

¹⁶ The inflated return due to the bid-ask spread as described in Blume and Stambaugh (1993) does not pose substantial problems to our equally weighted daily portfolios. The daily portfolio consists of 400-500 stocks on average. The portfolio diversification effect drastically reduces the possibility of inflated return. Take a numerical example. According to Figure 1 of Hasbrouck (2009), the 95 percentile of bid-ask spread is below 5%. Suppose the spread is 5%, half of the spread will be 2.5%. If further divided by 500 stocks, half the spread will be 0.005%. The square of that times 365 gives us 0.0091 basis points inflated return per year, which is only negligible.

the buy recommendation stocks have greater returns than sell recommendation stocks, suggesting that analysts' recommendations have investment values to the investors. But we are concerned about whether pessimistic analysts issue better recommendations. The numbers reported in the table have been converted into monthly terms. We find that the stocks to sell as recommended by pessimistic analysts have insignificantly lower returns of 13 basis points per month versus optimistic analysts. The stocks to buy as recommended by pessimistic analysts have significantly larger returns of 22 basis points per month relative to optimistic analysts. The hedge portfolio (buy-sell) within the pessimistic analysts has a larger mean return than that within the optimistic analysts. The return difference is 35 basis points, an equivalent of 4.2 percent per year. It appears that pessimistic analysts issue better recommendations, especially when it comes to the recommendation to buy stocks.

We use risk factor models to filter out the risk exposure of the portfolios. After risk adjustment, the average returns are similarly distributed across portfolios as before. The conclusion remains unchanged. Both the buy and sell recommendations issued by pessimistic analysts are significantly more profitable. We note that the average number of stocks involved in the portfolios is from 400 to 500.

In Panel B, we divide analysts into quintiles according to the pessimism measure. We find that the return differential is 18 basis points per month for the buy recommendation stocks, 27 basis points per month for the hedge portfolio (buy-sell), translated into an annual rate of 2.16 percent and 3.24 percent, respectively.

Panel C use the pessimism measure four quarters ago ($Q-4$), the return difference disappears. We will revisit the issue of lagged analyst type in later sections.

IV.2 Calendar portfolio approach of Fang and Yasuda (2011)

By the approach of Fang and Yasuda (2011), we essentially form daily calendar-time long and short portfolios based on new stock recommendations or recommendation revisions. If a new recommendation shows or there is a recommendation change, it is time to buy or sell the stock. The stock is bought when the I/B/E/S rating is 1 or 2, and sold when I/B/E/S rating is 3, 4 or 5. As new recommendations come from different analysts, which we have labeled as *pessimistic*, *neutral* and *optimistic*, we form two distinct *buy* and *sell* portfolios within each group of analysts according to the within group recommendation revisions from 1994 to 2009.

The daily portfolio starts by making an initial investment of \$1 on stock i_n because of a new recommendation or revision on date $recdat$.¹⁷ If the stock is held for t days, the investor earns the cumulative return denoted as

$$(8) \quad X_{n,t} = R_{i_n,recdat} * R_{i_n,recdat+1} * \dots * R_{i_n,t},$$

where $R_{i_n,t}$ is the total return of stock i_n on date t .

On date t , there exist multiple stocks in the buy or sell portfolio. The date- t portfolio return is given by

$$(9) \quad R_{p,t} = \frac{\sum_{n=1}^{N_{p,t}} X_{n,t-1} R_{i_n,t}}{\sum_{n=1}^{N_{p,t}} X_{n,t-1}},$$

where $R_{p,t}$ is the portfolio return on date t , $N_{p,t}$ is the number of stocks held in the portfolios, and $X_{n,t-1}$ is the weight that correctly calculates the value-weighted return. We set the number of days (T) to hold positions to 30 days as in Fang and Yasuda (2011). Obviously, this weight is \$1 when $t = 1$, it is zero when $t > T$, and it is the cumulative return from date $recdat$ to date $t-1$ as calculated in Eq. (7) when $0 < t \leq T$.

¹⁷This induces a look-ahead bias as the announcement return is included. We commence the portfolio one day after the announcement date (from day 2) and find the results are qualitatively similar. By sorting analysts into quintiles, the revisions of pessimistic analysts are more profitable by 37 basis points per month before risk adjustment and 44 basis points per month after four risk factors adjustment, which is approximately half of the return spread we will show.

Table 4 is about here.

The daily returns are collected for the *buy* and *sell* portfolios. From Panel A of Table 4, we find the recommendation to buy stocks is significantly more profitable within pessimistic analysts than within optimistic analysts. The return differential is 59 basis points, an equivalent of 7.08 percent per year. We find that the revision to sell stocks is not significantly different across different groups of analysts.

Panel B divides analysts into quintiles. The return differential of interest is 58 basis points for the buy stocks newly recommended or revised to buy or strong buy by pessimistic analysts versus optimistic analysts. Panel C uses the analyst type lagged four quarters to rank analysts into quintiles. We find that both lagged measures of analyst pessimism are positively associated with relative profitability of the stocks they revise to buy.

We examine cumulative abnormal stock returns from one day before the revision date to 20 days after the revision date. The abnormal stock return is the raw stock return minus the market return. We sort analysts into terciles by the measure of pessimism. The revisions fall into either the buy or the sell type as described above.

Figure 2 is about here.

From Graph A of Figure 2, stocks revised to buy earn positive returns whereas stocks revised to sell realize negative returns. We then form a hedge portfolio among pessimistic analysts by buying the stocks they revise to buy and selling the stocks they revise to sell. We also form a similar hedge portfolio among optimistic analysts. The return difference between the two portfolios is plotted in Graph B. We note that the revisions of pessimistic analysts are more profitable than that of pessimistic analysts during the whole event period, of which 50% is realized from day -1 to day 4, and the rest of which is realized from day 5 to day 20.

IV.3 Regression approach of Jegadeesh, Kim, Kriscic and Lee (2004)

In this sub-section, we use the quarterly regression framework of Jegadeesh et al. (2004). In particular, we use the A5 model in their Table VIII, where they show the consensus recommendation is uninformative about future stocks returns, but the change in consensus recommendation is. The dependent variable is the six-month cumulative future stock return adjusted for the market return represented by CRSP value weighted index. Because the six-month return is used in a dataset of quarterly frequency, the residuals of Fama-Macbeth regression may be correlated. Following Jegadeesh et al. (2004), we report the Newey-West adjusted t -statistics with the lag of 1.

Control variables used in the model are as follows. *Size* is the market value of the firm equity. *RETP* and *RET2P* are accumulative returns from month -6 to -1, and month 12 to -7, respectively, adjusted for the market return. *FREV* is the average consensus earnings forecast revision in the past six months, from month -5: month 0. *SUE* is the decile rank of earnings surprise, which is the change of earnings per share over that of four quarters ago divided by the standard deviation of earnings per share in the previous eight quarters. *EP* is the earnings to price ratio. *BP* is the book-to-market ratio. *TURN* is the average turnover ratio in the past six months; *LTG* is the long-term growth rate from I/BE/S; *SG* is the sales growth rate; *ACCR* is the total accruals divided by total assets; *CAPEX* is the total capital expenditures divided by total assets.

We use the daily analyst-firm-return dataset and divide into three sub-samples by analyst type. We then turn the dataset into the quarterly frequency. The consensus recommendation at the beginning of the quarter and the change of consensus recommendation over last quarter are calculated. As a result, within each analyst-type sub-sample, we have a quarterly firm-return dataset, with the key explanatory variables, consensus recommendation and the change in consensus recommendation, and other control variables. Note that the quintile ranks of the two key explanatory are used as in Jegadeesh et al. (2004).

Table 5 is about here.

We first filter out observations from the daily analyst-firm-return dataset with I/B/E/S sell and strong sell ratings. These two ratings constitute only a small percentage of the whole sample (less than 8%). The previous univariate analysis suggests that analyst pessimism may be important in distinguishing valuable recommendations only among the buy recommendations or the revisions to buy or strong buy. Table 5 shows that the average recommendation level is significant in predicting stock returns among the pessimistic analyst sub-sample, whereas in the optimistic analyst sub-sample it is not. The change in consensus recommendation is informative across the board, confirming the main conclusion of Jegadeesh et al. (2004) that the change in consensus recommendation is informative whereas the average recommendation may just be a mirror of momentum variables. Next, we do not filter out observations with I/B/E/S sell and strong sell ratings and repeat the preceding analysis. We find similar pictures. The average recommendation level is most significant in the pessimistic analyst sub-sample (t -value=3.31). The average recommendation is only marginally significant in the optimistic sub-sample, with a t -value of 1.98.

Panel B and Panel C lag the analyst type measure by four quarters and eight quarters, respectively, and repeat the analysis in Panel A. Overall, the stock recommendations issued by pessimistic analysts are more informative compared with neutral analysts and optimistic analysts. The fact that the lagged analyst type still produces differential recommendation profitability with respect to analyst pessimism suggests that pessimism seems to be a persistent trait of analysts.

IV.4 Regression approach of George and Hwang (2010)

In this sub-section, we use the regression framework of George and Hwang (2010) because this approach is arguably better at capturing the sole effect of variables of interest and the regression results have nice calendar portfolio implications.¹⁸ The dataset used for this approach is of the monthly frequency.

¹⁸This approach is invented in George and Hwang (2004), which is motivated by Fama (1976).

We run the following monthly regression from 1994 to 2009 and obtain parameter estimates for the independent variables:

$$(10) \quad R_{i,t} = b_{0,j,t} + b_{1,j,t} * Buy_{i,t-j} + b_{2,j,t} * Sell_{i,t-j} + control_X_{i,t-1} + \epsilon_{i,j,t},$$

Note that $R_{i,t}$ is the return of stock i in month t . $Buy_{i,t-j}$ is the dummy variable taking the value of 1 if the consensus recommendation (or monthly change in consensus recommendation) of stock i is in the top tercile rank j months ago. $Sell_{i,t-j}$ is the dummy variable taking the value of 1 if the consensus recommendation (or monthly change in consensus recommendation) of stock i is in the bottom tercile rank j months ago. The $control_X_{i,t-1}$ is a list of control variables known at the beginning of the month as listed in Table 5 and j is the lag of months ($j=1, 2, 3 \dots$).

Suppose $j=1$, the coefficient estimate of $b_{0,1,t}$ is the return to a stock portfolio that has neutralized the effect of all the firm characteristics and has zero values for dummy variables. A common stock that is ordinary in every respect in terms of firm characteristics represented by the control variables would earned such a return.¹⁹ The coefficient estimate of $b_{1,1,t}$ is the extra return above the ordinary return due to exposure to the dummy variable $Buy_{i,t-1}$. For a stock in the top tercile rank of the consensus recommendation level (or monthly change in consensus recommendation) one month ago, $Buy_{i,t-1}$ will be 1 and this stock obtains such an extra return. The estimate for $b_{0,1,t} + b_{1,1,t}$ is then the return to a portfolio of stocks formed one month ago that has the bottom tercile rank of consensus recommendation (or monthly change in consensus recommendation) and has neutralized the effect of all the other control variables. Similar interpretations can be given to $b_{2,1,t}$ and $b_{0,1,t} + b_{2,1,t}$. The estimate for $b_{1,1,t} - b_{2,1,t}$ is the hedge portfolio with both long (buy) and short (sell) positions.

Table 6 is about here.

¹⁹ Rigorously speaking, the historical average stocks return (equally weighted) is equal to the simple average of the intercept and the coefficients on dummy variables.

In Table 6, the parameter estimates reported in the column $K=k$ ($k=1, 3, 6, 9, 12, 18, 24$) is the average of parameter estimates from the above regression from $j=1$ to k . The $\sum_{j=1}^k (b_{0,j,t} + b_{1,j,t})$ is interpreted as the total return to a portfolio that renews $1/k$ of itself every month according to the tercile rank value of the stock consensus recommendation level (or monthly change in consensus recommendation) in last month. In other words, the long position stocks are of the top tercile in terms of the stock consensus recommendation level (or monthly change in consensus recommendation) last month, and the short position stocks are the bottom tercile in terms of the stock consensus recommendation level (or monthly change in consensus recommendation) last month.

Once new stocks become part of the portfolio, they stay for k months. $\sum_{j=1}^k b_{1,j,t}$ is the return to such a strategy to buy stock and $\sum_{j=1}^k b_{2,j,t}$ is the return to such a strategy to sell stocks (short position). $\sum_{j=1}^k (b_{1,j,t} - b_{2,j,t})$ is the return to the hedge portfolio (buy-sell). Since the coefficients represent portfolio returns, we further adjusted for risk exposure using contemporaneous monthly risk factors in a way similar to Eq. (6). We use the Carhart four-factor model.

Like in previous sections, we sort analysts into three groups, *pessimistic*, *neutral* and *optimistic*. Within the sub-sample of each analyst type we run the regression of Eq. (9). Panel A reports the raw estimates without adjusting for risk factors for buying or selling stocks based on the consensus recommendation level. We find that the return of the hedge portfolio when the holding period is one month ($k=1$) declines from 82 basis points in the pessimistic analyst group to 57 basis points in the optimistic analyst group. Judging from the coefficient estimates in the buy and sell rows, the buy recommendation of pessimistic analysts is much more useful than that of neutral and optimistic analysts, whereas the sell recommendation is only mildly superior to optimistic analysts. Also notable is that when the holding period is extended beyond one month ($k=3, 6, 9, 12, 18, 24$) buy recommendations of pessimistic analysts continue to be more profitable than that of optimistic analysts. Panel B adjusts the coefficient estimates for risk factors. The main

conclusion remains unchanged: Pessimistic analysts issue stock recommendations that are more profitable. In addition, the buy recommendations of pessimistic analysts are relatively more informative, confirming the prior findings in Table 3 and 4.

Panel C determines the buy and sell stocks according to the monthly change in the consensus recommendation level. We find that the return of the hedge portfolio when the holding period is one month ($k=1$) declines from 126 basis points in the pessimistic analyst group to 57 basis points in the optimistic analyst group. The two numbers are greater than the corresponding figures in Panel A, confirming the conclusion of Table 5 as well as the finding of Jegadeesh et al. (2004) that the recommendation revision is more informative than the recommendation level. The conclusion remains robust when the holding period extends beyond one month, and when the raw estimates are adjusted for risk factors.

IV.5 Discussion of the conditional pessimistic measure of Hugon and Muslu (2010)

Hugon and Muslu (2010) put forward another concept of analyst pessimism. That is, whether analysts respond more to bad news than peers do. In this sub-section, we test if their measure of analyst pessimism produces differential profitability of stock recommendation among analysts.

We follow Hugon and Muslu (2010) and compute their conditional and relative measure of analyst pessimism as the estimate of $(\beta_2 + \beta_1)/\beta_1$ for the following regression model:

$$(11) \quad Rev_{i,j,t} = \alpha_{0,t} + \alpha_{1,j,t} * Badnews_{i,j,t} + \beta_{0,j,t} * avgRev_{i,j,t} + \beta_{1,j,t} * (avgRev_{i,j,t} * Badnews_{i,j,t}) + \epsilon_{i,j,t},$$

where $Rev_{i,j,t}$ is analyst i 's forecast revision, defined as her earnings forecast of stock j at time t minus the mean consensus forecast scaled by stock price; $avgRev_{i,j,t}$ is the average forecast revision of the two analysts surrounding analyst i ; $Badnews_{i,j,t}$ is a dummy variable taking the value of 1 if $avgRev_{i,j,t}$ is negative. $(\beta_0 + \beta_1)/\beta_0$ measures the degree of analyst i 's

responsiveness to bad news versus good news. Regressions are performed annually to obtain the yearly pessimism measure for each analyst.

Table 7 is about here.

In Panel A of Table 7, we first replicate the main table (their Table 5) of Hugon and Muslu (2010). We confirm that the market response to earnings forecast revision is larger for pessimistic analysts. We use the methodology of both Table 3 and Table 4 to examine whether the pessimism measure of Hugon and Muslu (2010) relates to stock recommendation profitability. From Table 7, we find that their measure of analyst pessimism is positively associated with sell recommendations or revisions, but not with buy recommendations or revisions. This result is intuitive as the pessimism measure of Hugon and Muslu (2010) is on how responsive analysts react to bad news.

IV.6 Discussion of ex-ante forecast accuracy and recommendation profitability

Loh and Mian (2006) find a contemporaneous relationship between earnings forecast accuracy and profitability of stock recommendations.²⁰ On the other hand, Hall and Tacon (2010) show analysts who made accurate earnings forecasts in the prior year or quarter do not necessarily make recommendations that are more profitable. We further test the idea to make sure that our finding does not result from ex-ante forecast accuracy. Our methodology is different from Hall and Tacon (2010). Therefore, our analysis complements their study.

We create an ex-ante measure of forecast accuracy, which is obviously different from Loh and Mian (2006). We use the absolute value of earnings forecast away from consensus before the earnings announcement date (*DIST*) to rank analysts as in Eq. (3). The resulting measure is an ex-ante measure of earning forecast accuracy.

Table 8 is about here.

²⁰ Their measure of earnings forecast accuracy is not ex-ante. They do not rule out the possibility that their finding is an empirical artifact.

We use the methodology of both Table 3 and Table 4 to examine how this measure is related to stock recommendation profitability. In Panel A of Table 7, we do not find the ex-ante measure of earnings forecast accuracy is positively associated with stock recommendations or recommendation revisions.²¹ In Panel B, most accurate analyst issue more profitable revisions to sell, but not revisions to buy.

V. Conclusion

We hypothesize that pessimistic analysts deliver more profitable stock recommendations or recommendation revisions to the investors. On the one hand, pessimistic analysts may unwind general optimism bias in earnings forecast. On the other hand, they are subject to less distorted incentives.

We construct an ex-ante measure of analyst pessimism based on the analysts' earnings forecasting behaviors before the announcement date. We find that stock recommendations or recommendation revisions are more profitable when they come from pessimistic analysts rather than optimistic analysts.

During the analysis, we lag analyst type by four quarters or eight quarters and still observe differential profitability in recommendations or recommendation revisions between pessimistic and optimistic analysts. This suggests analysts do differ in terms of pessimism, as suggested by Hugon and Muslu (2010) that analyst pessimism is rationally determined in the analyst labor market. We further find that our finding does not result from the conditional pessimism measure of Hugon and Muslu (2010) or another ex-ante measure of forecast accuracy.

²¹ Loh and Mian (2006) do not find that the contemporaneous relationship between earnings forecast accuracy and profitability of recommendations is driven by analyst optimism. Their measure of analyst optimism is likely a contemporaneous measure (not clear from the text). Moreover, it is not an ex-ante measure as they regard analyst optimism as earnings forecasts higher than the subsequently announced actual earnings.

Our study has limitations though. It is not clear whether cognitive bias or incentive bias is driving our finding. Further studies are needed to find which one is a major cause of our finding. To this end, it is important to find the relations between analyst pessimism and forecast accuracy. It is also important to find how regulation changes (e.g., regulation FD, global settlement) affect relative recommendation profitability associated with analyst pessimism. It is interesting to examine how pessimism develops among analysts, and their career outcomes.

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Appendix A: Variable List

<i>Variable</i>	<i>Definition</i>
DIST	An analyst's earnings forecast away from consensus, defined as the individual earnings forecast minus the mean forecast divided by the standard deviation of all forecasts.
avgDIST	Analyst's average forecast distance from consensus in the prior four quarters
Pessi	An ex-ante quarterly measure of pessimism for security analysts based on their forecasting behaviors before the earnings announcement date in the previous four quarters.
ME	Market equity, a proxy for firm size
RETP	Cumulative market-adjusted return for the preceding six months (month -6 to -1) as in Jegadeesh et al. (2004).
RET2P	Cumulative market-adjusted return for the second preceding six months (month -12 to -7) as in Jegadeesh et al. (2004).
FREV	Mean forecast revision in the past six months (month -5: 0) as in Jegadeesh et al. (2004).
SUR	Standardized unexpected earnings surprise, defined as EPS in quarter t minus EPS in quarter $t-5$ divided by the standard deviation of the preceding eight quarters.
EP	Earnings to price ratio, defined as EPS divided stock price. EPS are the sum of most recent four quarters, and the price is as of last month end.
BP	Book-to-market equity ratio. The book equity is as of last fiscal year end, and the market equity is as of last month end.
TURN	Average monthly turnover in the last 6 months. Monthly turnover is defined as total shares trades in this month divided by total shares outstanding.
ACCR (%)	Total accruals to total assets ratio. The total accruals are defined as $[(\Delta \text{Current Assets} - \Delta \text{Cash}) - (\Delta \text{Current Liabilities} - \Delta \text{Short-term Debt}) - \Delta \text{Taxes Payable}) - \text{Depreciation and Amortization Expenset}]/\text{Total assets}$.
CAPEX (%)	Capital expenditure. Total capital expenditures divided by total assets of the firm. Note that in Compustat the quarterly capital expenditure item is a rolling sum of all previous quarters in the same fiscal year. Adjustments are made as in Jegadeesh et al (2004).
SG	Sales growth. Rolling sum of sales for the preceding four quarters divided by the same figure one year ago, defined in the same way as in Jegadeesh et al. (2004).
BM	Book-to-market equity ratio. The book equity is as of last fiscal year end, and the market equity is as of last month end.
BETA	Market beta, estimated as in Fama and French (1992).
INST (%)	Institutional ownership, the most recently observable institutional ownership according to the Thompson/13F dataset.
Buy	A dummy variable suggesting a buy signal in the George and Hwang (2010) regression.
Sell	A dummy variable suggesting a sell signal in the George and Hwang (2010) regression.
REV	An analyst's forecast revision in obtaining the measure of Hugon and Muslu (2010), defined as individual forecast minus mean forecast divided by the stock price at the beginning of the month.
avgREV	The average REV values of two analysts surrounding this analyst.
BadNews	A dummy variable indicating that avgREV is negative.

Table 1: Sample Selection

This table describes our sample selection process. The number of observations, unique analysts and stocks are provided. The calendar portfolio test refers to forming calendar portfolio based on the daily average recommendation level as in Barber et al. (2001), or the recommendation revision as in Fang and Yasuda (2011). The regression test refers to the quarterly Fama-Macbeth regression as in Jegadeesh et al. (2004), or the monthly *J-K* regression framework as in George and Hwang (2010).

	# of observations (# of unique analyst) [# of unique stock]	
	calendar portfolio test	regression test
1. I/B/E/S earnings forecasts of U.S. stocks, 1980-2009	13,684,880 (18,965) [16,368]	
1.1. I/B/E/S earnings forecasts of U.S. stocks, 1992-2009	11,731,205 [14,812] (13,878)	
1.2. Quarterly measures of analyst pessimism, 1994-2009 (analyst-quarter)	120,972 (7,236) n.a.	
2. I/B/E/S recommendations of U.S. stocks, 1994-2009	495,637 (12,821) [13,190]	
2.1. Merge 2 with CRSP daily stock file to create daily recommendation, 1994-2009 (analyst-firm-date)	50,227,336 (13,149) [13,144]	
3. Merge 1.2 with 2.1, and further require common stocks and larger than \$5 stock price (analyst-firm-date)	28,732,325 (5,872) [9,606]	
3.1. Subset of 3 with recommendation revision, 1994 to 2009 (analyst-firm-date)	1,656,564 (5,010) [9,212]	
4. Merge 3 with CRSP monthly stock returns and other control variables, 1994 to 2009 (analyst-firm-month)		27,225,664 (5,854) [7,797]

Table 2: Descriptive statistics

This table provides descriptive statistics on the measure and the regression sample stocks. Each quarter we sort the population of analysts into three groups, *Pessimistic*, *Neutral* and *Optimistic*, based on their earnings forecast behaviors in the previous four quarters. Panel A provides the transition matrix of analyst type from quarter Q to quarter $Q+1$, $Q+4$, and $Q+8$. Panel B provides distribution of recommendations by analyst type (I/B/E/S rating: 1=strong buy, 2=buy, 3=held, 4=sell, 5=strong sell). Row percentages are provided below the frequency numbers. Panel C provides distribution of recommendation revisions by analyst type. Two-way percentages are provided under the frequency numbers. Panel D provides descriptive statistics on the regression sample by analyst type.

Panel A: Transition matrix of analysts

$Q \setminus Q+1$	Pessimistic	Neutral	Optimistic	N
Pessimistic	80%	20%	1%	41,346
Neutral	21%	59%	21%	40,081
Optimistic	1%	21%	78%	37,166
	Total			118,593
$Q \setminus Q+4$	Pessimistic	Neutral	Optimistic	N
Pessimistic	52%	30%	18%	36,639
Neutral	32%	37%	31%	34,747
Optimistic	19%	30%	51%	31,714
	Total			103,100
$Q \setminus Q+8$	Pessimistic	Neutral	Optimistic	N
Pessimistic	46%	30%	24%	29,332
Neutral	34%	34%	32%	27,166
Optimistic	27%	30%	43%	24,772
	Total			81,270

Panel B: Recommendation distribution by analyst type

Analyst type $Q \setminus$ IBES Rating Q	5	4	3	2	1	Total
Pessimistic	3,602	6,505	57,072	40,093	31,695	131,253
	3%	5%	41%	29%	23%	
Neutral	2,531	5,076	45,990	35,162	27,492	116,251
	2%	4%	40%	30%	24%	
Optimistic	2,915	4,848	42,852	32,832	27,761	111,208
	3%	4%	39%	30%	25%	

Panel C: Recommendation revision distribution by analyst type

Recommendation revision $Q \setminus$ Analyst type Q		Pessimistic	Neutral	Optimistic
-4		333	245	280
		0%	0%	0%
-3		332	349	361
		0%	0%	0%
-2		15,663	12,101	11,761
		6%	5%	4%
-1		28,577	23,804	21,354
		11%	9%	8%
0		23,453	19,027	18,019
		9%	7%	7%
1		23,950	19,277	17,262
		9%	7%	6%
2		12,822	9,352	8,960
		5%	3%	3%
3		232	193	191
		0%	0%	0%
4		245	117	205
		0%	0%	0%

Panel D: Statistics of the quarterly regression sample by analyst type

	Pessimistic				Neutral				Optimistic			
	N	Mea n	Std	Media n	N	Mea n	Std	Media n	N	Mea n	Std	Media n
RET (%)	80,59				75,61				70,92			
	1	0.52	14.50	0.35	3	0.55	14.82	0.40	8	0.63	14.74	0.46
ME	80,59	5,77	14,94		75,61	5,86	15,18		70,92	6,19	15,83	
	1	1	3	1,190	3	3	4	1,160	8	6	6	1,218
REV (%)	75,55	-			70,78	-			66,50	-		
	9	0.04	1.20	0.01	5	0.04	1.19	0.01	6	0.03	1.18	0.01
SUR	78,47				73,55				68,87			
	2	4.54	2.83	5.00	4	4.57	2.83	5.00	0	4.60	2.84	5.00
EP	80,17				75,17				70,44			
	5	0.02	0.09	0.04	6	0.02	0.09	0.04	7	0.02	0.09	0.04
BM	80,59				75,61				70,92			
	1	0.52	0.38	0.44	3	0.50	0.37	0.42	8	0.49	0.36	0.41
TURN	80,59				75,61				70,92			
	1	0.19	0.18	0.13	3	0.19	0.18	0.13	8	0.19	0.18	0.13
LTG	75,08				69,25				64,85			
	0	0.15	0.27	0.12	1	0.17	0.28	0.14	3	0.18	0.28	0.14
ACCR (%)	77,64				72,78				68,05			
	6	3.28	13.02	1.79	7	3.98	14.15	2.05	1	4.10	14.29	2.09
CAPEX (%)	71,55				67,39				62,56			
	8	1.70	2.13	1.06	0	1.76	2.20	1.09	2	1.81	2.26	1.11
BETA	80,59				75,61				70,92			
	1	1.22	0.37	1.18	3	1.24	0.38	1.19	8	1.23	0.38	1.19
INST (%)	80,59	63.0			75,61	62.6			70,92	62.0		
	1	5	23.47	65.44	3	5	23.62	65.01	8	4	23.72	64.43

Table 3: Calendar portfolio approach of Barber et al. (2001)

This table presents average returns of daily calendar portfolio of stocks sorted by the average recommendation level from 1994 to 2009 as in Barber et al. (2001). The daily portfolio returns have been compounded into monthly returns. *Raw* is raw stock return. *Alpha3f* is the alpha from the Fama-French three-factor model. *Alpha4f* is the alpha from the Carhart four-factor model. Each quarter we sort the population of analysts into three groups, *Pessimistic*, *Neutral* and *Optimistic*, based on their earnings forecast behaviors in the previous four quarters. Within each group of analysts, we sort the stocks they cover into three daily portfolios, *Sell*, *Hold* and *Buy*, based on the average recommendation level. The *t*-values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Average return of the portfolios

		Sell	Hold	Buy	Buy-Sell
Raw	Pessimistic	0.51	1.00	1.32	0.81***
		(1.2)	(2.23)	(2.89)	(5.68)
	Neutral	0.59	1.02	1.25	0.66***
		(1.4)	(2.18)	(2.61)	(3.39)
	Optimistic	0.63	0.91	1.10	0.47***
		(1.45)	(2.02)	(2.27)	(2.72)
Alpha3f	Pessimistic	-0.13	0.08	0.22**	0.35***
		(-1.47)	(0.85)	(2.54)	(2.96)
	Neutral	-0.48	0.05	0.44	0.91***
		(-3.93)	(0.46)	(4.84)	(9.04)
	Optimistic	-0.36	0.12	0.40	0.76***
		(-2.72)	(1.16)	(4.05)	(6.25)
Alpha4f	Pessimistic	-0.32	0.16	0.44	0.76***
		(-3.33)	(1.62)	(4.76)	(8.51)
	Neutral	-0.18	0.20	0.43	0.61***
		(-1.83)	(2.09)	(4.07)	(6.19)
	Optimistic	-0.14	0.13	0.25	0.38***
		(-1.48)	(1.31)	(2.48)	(4.28)
Alpha5f	Pessimistic	-0.16*	-0.01	0.21***	0.37***
		(-1.89)	(-0.06)	(2.9)	(3.13)
	Neutral	-0.32	0.16	0.44	0.76***
		(-3.33)	(1.62)	(4.76)	(8.51)
	Optimistic	-0.18	0.20	0.43	0.61***
		(-1.83)	(2.09)	(4.07)	(6.19)
Alpha6f	Pessimistic	-0.14	0.13	0.25	0.38***
		(-1.48)	(1.31)	(2.48)	(4.28)
	Neutral	-0.18**	0.03	0.20***	0.38***
		(-2.2)	(0.34)	(2.64)	(3.18)
	Optimistic	-0.16*	-0.01	0.21***	0.37***
		(-1.89)	(-0.06)	(2.9)	(3.13)
<hr/>					
Average number of stocks in the portfolios		Sell	Hold	Buy	
Pessimistic		554.23	430.66	479.58	
Neutral		508.40	395.88	446.91	
Optimistic		475.10	394.35	399.94	

Panel B: Analysts are sorted into quintiles by pessimism measure Q

		Sell	Hold	Buy	Buy-Sell
<i>Alpha4f</i>	1=most pessimistic	-0.21 (-1.7)	0.21 (1.97)	0.41 (3.92)	0.62*** (5.24)
	2	-0.27 (-2.48)	0.13 (1.12)	0.37 (3.72)	0.64*** (6.04)
	3	-0.13 (-1.14)	0.18 (1.49)	0.43 (3.72)	0.56*** (4.9)
	4	-0.16 (-1.48)	0.27 (2.45)	0.29 (2.67)	0.45*** (3.77)
	5=least pessimistic	-0.11 (-0.94)	0.10 (1.03)	0.24 (2.14)	0.35*** (2.75)
	1 - 5	-0.10 (-0.8)	0.10 (0.91)	0.18* (1.82)	0.27* (1.77)

Panel D: Analysts are sorted into quintiles by pessimism measure $Q-4$

		Sell	Hold	Buy	Buy-Sell
<i>Alpha4f</i>	1=most pessimistic	-0.27 (-2.34)	0.18 (1.63)	0.28 (2.43)	0.54*** (4.42)
	2	-0.19 (-1.51)	0.10 (0.97)	0.33 (2.69)	0.51*** (3.97)
	3	-0.07 (-0.58)	0.35 (2.75)	0.42 (3.22)	0.49*** (3.34)
	4	-0.20 (-1.91)	0.19 (1.61)	0.31 (2.78)	0.51*** (4.24)
	5=least pessimistic	-0.21 (-2.14)	0.34 (3.01)	0.26 (2)	0.47*** (3.76)
	1 - 5	-0.06 (-0.56)	-0.16 (-1.42)	0.02 (0.13)	0.07 (0.4)

Table 4: Calendar portfolio approach of Fang and Yasuda (2011)

This table presents average returns of daily calendar portfolio of stocks sorted by the average recommendation level from 1994 to 2009 as in Fang and Yasuda (2011). The daily return in percentage is multiplied by 21 to represent monthly return. *Raw* is raw stock return. *Alpha3f* is the alpha from the Fama-French three-factor model. *Alpha4f* is the alpha from the Carhart four-factor model. Each quarter we sort the population of analysts into three groups, *Pessimistic*, *Neutral* and *Optimistic*, based on their earnings forecast behaviors in the previous four quarters. Within each group of analysts, we sort the stocks they cover into two daily portfolios, *Sell* and *Buy*, based on new recommendations or recommendation revisions. The *t*-values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Average returns of the portfolios

		Sell	Buy	Buy-Sell
<i>Raw</i>	Pessimistic	-2.45 (-5.12)	3.09 (6.7)	5.56*** (31.69)
	Neutral	-2.80 (-5.79)	2.84 (6.02)	5.63*** (30.01)
	Optimistic	-2.43 (-4.87)	2.51 (5.2)	4.94*** (25.2)
	Pessimistic-Optimistic	-0.02 (-0.14)	0.59*** (3.98)	0.62*** (3.38)
<i>Alpha3f</i>	Pessimistic	-3.20 (-17.47)	2.47 (19.76)	5.67*** (33.05)
	Neutral	-3.50 (-18.17)	2.25 (17.95)	5.75*** (31.65)
	Optimistic	-3.10 (-14.59)	1.95 (13.63)	5.06*** (26.24)
	Pessimistic-Optimistic	-0.10 (-0.56)	0.52*** (3.65)	0.61*** (3.31)
<i>Alpha4f</i>	Pessimistic	-2.97 (-18.81)	2.54 (20.33)	5.51*** (34.85)
	Neutral	-3.29 (-18.94)	2.30 (18.42)	5.59*** (32.68)
	Optimistic	-2.84 (-15.45)	2.04 (14.37)	4.88*** (27.65)
	Pessimistic-Optimistic	-0.14 (-0.78)	0.50*** (3.48)	0.63*** (3.41)

Average number of stocks in the portfolios	Sell	Buy
pessimistic	220.53	248.51
neutral	178.74	214.18
optimistic	164.16	204.10

Panel B: Analysts are sorted into quintiles by pessimism measure Q

		Sell	Buy	Buy-Sell
<i>Alpha4f</i>	1=most pessimistic	-2.85 (-16.47)	2.64 (18.48)	5.49*** (30.93)
	2	-3.30 (-17.45)	2.39 (17.03)	5.69*** (28.42)
	3	-3.13 (-15.93)	2.28 (15.6)	5.41*** (27.05)
	4	-3.51 (-16.95)	2.12 (14.27)	5.64*** (25.78)
	5=least pessimistic	-2.42 (-11.51)	2.06 (12.37)	4.48*** (22.39)
	1 - 5	-0.43* (-1.89)	0.58*** (3.2)	1.01*** (4.43)

Panel D: Analysts are sorted into quintiles by pessimism measure $Q-4$

		Sell	Buy	Buy-Sell
<i>Alpha4f</i>	1=most pessimistic	-3.08 (-16.07)	2.49 (17.14)	5.58*** (27.87)
	2	-3.19 (-16.2)	2.25 (14.18)	5.45*** (25.93)
	3	-3.12 (-14.51)	2.41 (15.4)	5.53*** (24.09)
	4	-3.06 (-14.73)	2.44 (15.6)	5.50*** (24.78)
	5=least pessimistic	-2.83 (-12.27)	2.12 (12.53)	4.94*** (22)
	1 - 5	-0.26 (-1.06)	0.38** (2.09)	0.64** (2.43)

Table 5: Regression approach of Jegadeesh et al. (2004)

This table reports quarterly regressions of future six-month market-adjusted stock returns (*FRET6*) on the consensus recommendation, the change in consensus recommendation and other control variables as listed Jegadeesh et al. (2004) from 1994:Q1 to 2009:Q4. QREV is the quintile rank of consensus recommendation at the beginning of each quarter. QCHGREV is the quintile rank of the change in consensus recommendation at the beginning of this quarter over the beginning of last quarter. The regression sample is divided by analyst type of quarter *Q*, *Q-4* and *Q-8*, respectively, for Panel A, B and C. The *t*-values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Analyst type *Q*

	IBES ratings (1, 2 ,3)							IBES ratings (1, 2 ,3, 4, 5)					
	Pessimistic		Neutral		Optimism			Pessimistic		Neutral		Optimism	
Intercept	8.750*	8.204	9.535*	9.281*	10.952**	10.484**		8.436*	8.171	8.792*	8.744*	10.130**	9.906**
	(1.77)	(1.66)	(1.90)	(1.87)	(2.27)	(2.14)		(1.71)	(1.66)	(1.80)	(1.78)	(2.12)	(2.04)
QCON	0.338***		0.203		0.218			0.425***		0.346**		0.332*	
	(3.06)		(1.56)		(1.34)			(3.14)		(2.01)		(1.93)	
QCHGCON		0.482***		0.336***		0.393***			0.444***		0.393***		0.418***
		(4.35)		(2.93)		(2.94)			(3.75)		(3.46)		(3.29)
ME	-0.347	-0.359	-0.304	-0.331	-0.541	-0.551		-0.334	-0.349	-0.289	-0.315	-0.507	-0.525
	(-0.99)	(-1.02)	(-0.88)	(-0.95)	(-1.50)	(-1.52)		(-0.96)	(-1.00)	(-0.85)	(-0.91)	(-1.43)	(-1.46)
RETP	0.015	0.013	0.019	0.016	0.017	0.015		0.016	0.014	0.018	0.015	0.017	0.015
	(0.56)	(0.47)	(0.72)	(0.59)	(0.67)	(0.55)		(0.60)	(0.50)	(0.67)	(0.54)	(0.65)	(0.56)
RET2P	-0.023	-0.021	-0.019	-0.015	-0.018	-0.017		-0.023	-0.021	-0.020	-0.017	-0.017	-0.016
	(-1.45)	(-1.22)	(-1.32)	(-1.00)	(-1.26)	(-1.17)		(-1.48)	(-1.25)	(-1.42)	(-1.11)	(-1.28)	(-1.11)
FREV	0.839***	0.947***	0.453	0.615	1.008***	0.952**		0.860***	0.953***	0.528	0.754*	0.978***	0.873**
	(3.02)	(2.98)	(1.30)	(1.52)	(2.85)	(2.51)		(3.18)	(3.12)	(1.57)	(2.00)	(2.72)	(2.26)
SUR	-0.024	-0.015	0.023	0.034	0.049	0.072		-0.023	-0.008	0.025	0.036	0.062	0.089
	(-0.32)	(-0.19)	(0.32)	(0.44)	(0.58)	(0.84)		(-0.31)	(-0.10)	(0.35)	(0.47)	(0.76)	(1.06)
EP	7.776	8.690	6.249	5.700	10.495*	10.918*		8.312	9.229*	6.166	5.649	10.181	10.087
	(1.45)	(1.63)	(1.00)	(0.89)	(1.68)	(1.73)		(1.61)	(1.79)	(1.00)	(0.90)	(1.63)	(1.57)
BP	-0.248	-0.454	-0.258	-0.346	-0.483	-0.647		-0.268	-0.478	-0.231	-0.331	-0.510	-0.694
	(-0.39)	(-0.71)	(-0.37)	(-0.50)	(-0.62)	(-0.81)		(-0.43)	(-0.75)	(-0.33)	(-0.48)	(-0.66)	(-0.88)
TURN	1.053	1.113	1.077	1.172	1.242	1.395		1.123	1.170	1.138	1.231	1.240	1.362
	(1.06)	(1.06)	(1.03)	(1.08)	(1.19)	(1.29)		(1.14)	(1.14)	(1.10)	(1.14)	(1.19)	(1.27)
LTG	0.296	0.183	-0.060	0.445	-0.542	-0.429		-0.030	-0.169	0.125	0.628	-0.626	-0.465
	(0.33)	(0.20)	(-0.06)	(0.46)	(-0.57)	(-0.42)		(-0.03)	(-0.18)	(0.13)	(0.68)	(-0.67)	(-0.46)
SG	-2.702**	-2.421**	-3.258***	-3.035***	-2.936***	-2.706***		-2.714**	-2.407**	-3.061***	-2.752***	-2.913***	-2.624***
	(-2.48)	(-2.22)	(-3.31)	(-3.22)	(-2.96)	(-2.78)		(-2.50)	(-2.22)	(-3.13)	(-2.93)	(-2.88)	(-2.68)
TA	-1.178	-1.663	-3.020	-3.455	-3.433*	-3.402*		-0.968	-1.452	-3.295	-3.673*	-3.483*	-3.564*
	(-0.55)	(-0.73)	(-1.52)	(-1.62)	(-1.73)	(-1.73)		(-0.45)	(-0.65)	(-1.66)	(-1.71)	(-1.76)	(-1.79)
CAPEX	-6.160	-6.493	-16.119	-15.073	-12.163	-14.161		-6.156	-6.948	-16.430	-15.540	-12.773	-14.479
	(-0.35)	(-0.36)	(-0.94)	(-0.86)	(-0.70)	(-0.79)		(-0.35)	(-0.38)	(-0.97)	(-0.89)	(-0.74)	(-0.82)
R ²	0.114	0.118	0.106	0.108	0.113	0.115		0.114	0.118	0.106	0.108	0.113	0.115
NOBS	59,563	56,416	55,014	51,905	51,048	47,967		61,433	58,278	56,819	53,698	52,761	49,670

Panel B: Analyst type Q -4

IBES ratings (1, 2 ,3)								IBES ratings (1, 2 ,3, 4, 5)					
	Pessimistic		Neutral		Optimism			Pessimistic		Neutral		Optimism	
Intercept	8.732*	8.940*	10.602**	10.620**	9.704*	8.845*		8.389*	8.701*	9.602*	9.823*	8.852*	8.635*
	(1.87)	(1.90)	(2.00)	(2.06)	(1.93)	(1.75)		(1.82)	(1.87)	(1.82)	(1.90)	(1.78)	(1.70)
QCON	0.437***		0.126		0.281**			0.492***		0.309		0.516***	
	(3.91)		(0.77)		(2.24)			(3.55)		(1.63)		(3.62)	
QCHGCON		0.468***		0.325**		0.380***			0.506***		0.375***		0.423***
		(3.78)		(2.56)		(2.99)			(4.03)		(2.79)		(3.32)
R ²	0.117	0.121	0.113	0.118	0.120	0.127		0.116	0.120	0.113	0.119	0.119	0.126
START	199404	199407	199404	199407	199404	199407		199404	199407	199404	199407	199404	199407
END	200910	200910	200910	200910	200910	200910		200910	200910	200910	200910	200910	200910
GROUP	63	62	63	62	63	62		63	62	63	62	63	62
NOBS	51,976	48,851	48,885	45,760	45,314	42,268		53,793	50,662	50,631	47,491	47,051	43,990

Panel B: Analyst type Q -8

IBES ratings (1, 2 ,3)								IBES ratings (1, 2 ,3, 4, 5)					
	Pessimistic		Neutral		Optimism			Pessimistic		Neutral		Optimism	
Intercept	9.153*	8.865*	9.771*	9.396	11.643**	11.088**		8.466*	8.301*	8.415	8.468	11.007**	10.647**
	(1.87)	(1.80)	(1.70)	(1.62)	(2.19)	(2.17)		(1.76)	(1.72)	(1.49)	(1.48)	(2.06)	(2.08)
QCON	0.470***		0.318**		0.189			0.613***		0.492***		0.285	
	(3.33)		(2.39)		(1.29)			(3.35)		(3.26)		(1.58)	
QCHGCON		0.372***		0.380***		0.166			0.373***		0.440***		0.144
		(3.89)		(3.13)		(1.22)			(3.72)		(4.16)		(1.08)
R ²	0.123	0.126	0.124	0.127	0.123	0.127		0.122	0.125	0.123	0.126	0.122	0.126
START	199504	199507	199504	199507	199504	199507		199504	199507	199504	199507	199504	199507
END	200910	200910	200910	200910	200910	200910		200910	200910	200910	200910	200910	200910
GROUP	59	58	59	58	59	58		59	58	59	58	59	58
NOBS	43,964	41,037	41,498	38,543	38,404	35,529		45,691	42,749	43,113	40,149	39,973	37,088

Table 6: The *J-K* regression approach of George and Hwang (2010)

For different lags in months, j ($j=1, 2, 3 \dots$), we run the following monthly regression from 1994 to 2009 and obtain parameter estimates for the independent variables:

$$R_{i,t} = b_{0,j,t} + b_{1,j,t} * Buy_{i,t-j} + b_{2,j,t} * Sell_{i,t-j} + control_X_{i,t-1} + \epsilon_{i,j,t}$$

where $R_{i,t}$ is the return of stock i in month t , $Buy_{i,t-j}$ is the dummy variable taking the value of 1 if the consensus recommendation (or change in consensus recommendation) of stock i is in the top tercile rank j months ago, $Sell_{i,t-j}$ is the dummy variable taking the value of 1 if the consensus recommendation (or change in consensus recommendation) of stock i is in the bottom tercile rank j months ago, and $control_X_{i,t-1}$ is a list of control variables known at the beginning of the month as listed in Table 5. The parameter estimates reported in the column $K=k$ ($k=1, 3, 6, 9, 12, 18, 24$) is the average of parameter estimates from the above regression from $j=1$ to k . Panel A report results on the recommendation level. Panel B adjusts the estimates in Panel A with risk factors. Panel C report results on the recommendation revision. Panel D adjusts the estimates in Panel C with risk factors. The t -values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Recommendation level - raw return

		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Pessimistic	Intercept	0.92** (2.27)	0.91** (2.24)	0.90** (2.21)	0.90** (2.20)	0.91** (2.23)	0.92** (2.25)	0.93** (2.27)
	Buy	0.39*** (4.79)	0.28*** (3.39)	0.27*** (3.19)	0.29*** (3.48)	0.28*** (3.40)	0.28*** (3.43)	0.29*** (3.53)
	Sell	-0.43*** (-5.67)	-0.30*** (-3.89)	-0.31*** (-3.93)	-0.30*** (-3.83)	-0.31*** (-3.95)	-0.32*** (-4.17)	-0.34*** (-4.43)
	Buy-Sell	0.82*** (9.72)	0.57*** (6.83)	0.57*** (6.53)	0.59*** (6.65)	0.59*** (6.62)	0.60*** (6.70)	0.62*** (6.97)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Neutral	Intercept	1.05** (2.56)	1.04** (2.51)	1.04** (2.52)	1.06** (2.59)	1.05** (2.58)	1.06** (2.58)	1.05** (2.56)
	Buy	0.14 (1.63)	0.00 (0.03)	0.00 (0.03)	0.03 (0.37)	0.06 (0.72)	0.08 (0.93)	0.10 (1.12)
	Sell	-0.60*** (-6.64)	-0.49*** (-5.37)	-0.50*** (-5.67)	-0.52*** (-6.00)	-0.51*** (-5.84)	-0.49*** (-5.65)	-0.48*** (-5.56)
	Buy-Sell	0.74*** (8.17)	0.49*** (5.25)	0.50*** (5.42)	0.55*** (6.07)	0.57*** (6.30)	0.57*** (6.24)	0.57*** (6.33)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Optimistic	Intercept	0.94** (2.26)	0.92** (2.22)	0.93** (2.25)	0.94** (2.26)	0.95** (2.29)	0.95** (2.29)	0.96** (2.31)
	Buy	0.21** (2.38)	0.13 (1.41)	0.13 (1.34)	0.13 (1.38)	0.12 (1.32)	0.13 (1.40)	0.14 (1.49)
	Sell	-0.36*** (-4.52)	-0.20** (-2.48)	-0.20** (-2.33)	-0.23** (-2.57)	-0.24*** (-2.76)	-0.26*** (-2.89)	-0.28*** (-3.10)
	Buy-Sell	0.57*** (6.80)	0.33*** (3.99)	0.32*** (3.59)	0.35*** (3.78)	0.37*** (3.91)	0.39*** (4.14)	0.42*** (4.48)

Panel B: Recommendation level - risk adjusted return

		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Pessimistic	Intercept	0.32*** (2.98)	0.31*** (2.83)	0.30*** (2.71)	0.30*** (2.64)	0.31*** (2.70)	0.31*** (2.71)	0.32*** (2.79)
	Buy	0.38*** (4.60)	0.26*** (3.24)	0.25*** (3.01)	0.27*** (3.26)	0.26*** (3.16)	0.27*** (3.21)	0.27*** (3.31)
	Sell	-0.41*** (-5.34)	-0.28*** (-3.62)	-0.29*** (-3.71)	-0.28*** (-3.62)	-0.29*** (-3.77)	-0.30*** (-3.95)	-0.32*** (-4.19)
	Buy-Sell	0.78*** (9.32)	0.54*** (6.43)	0.54*** (6.11)	0.55*** (6.21)	0.56*** (6.20)	0.57*** (6.30)	0.59*** (6.62)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Neutral	Intercept	0.47*** (3.76)	0.45*** (3.58)	0.46*** (3.60)	0.47*** (3.75)	0.47*** (3.70)	0.47*** (3.70)	0.47*** (3.64)
	Buy	0.16* (1.86)	0.03 (0.35)	0.03 (0.33)	0.06 (0.68)	0.09 (1.05)	0.11 (1.28)	0.13 (1.43)
	Sell	-0.59*** (-6.81)	-0.47*** (-5.42)	-0.49*** (-5.77)	-0.50*** (-6.06)	-0.49*** (-5.89)	-0.47*** (-5.68)	-0.46*** (-5.51)
	Buy-Sell	0.74*** (8.49)	0.50*** (5.55)	0.51*** (5.72)	0.56*** (6.48)	0.58*** (6.81)	0.58*** (6.73)	0.58*** (6.76)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Optimistic	Intercept	0.36*** (3.10)	0.34*** (2.88)	0.35*** (2.83)	0.35*** (2.83)	0.36*** (2.87)	0.37*** (2.91)	0.37*** (2.96)
	Buy	0.20** (2.23)	0.12 (1.31)	0.13 (1.31)	0.13 (1.31)	0.12 (1.25)	0.13 (1.28)	0.13 (1.36)
	Sell	-0.36*** (-4.45)	-0.19** (-2.27)	-0.17** (-2.01)	-0.20** (-2.24)	-0.21** (-2.42)	-0.23** (-2.56)	-0.25*** (-2.71)
	Buy-Sell	0.56*** (6.55)	0.30*** (3.73)	0.29*** (3.32)	0.32*** (3.46)	0.33*** (3.56)	0.35*** (3.77)	0.38*** (4.03)

Panel C: Recommendation revision - raw return

		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Pessimistic	Intercept	0.88**	0.87**	0.86**	0.87**	0.87**	0.87**	0.88**
		(2.22)	(2.20)	(2.18)	(2.19)	(2.21)	(2.21)	(2.23)
	Buy	0.69***	0.51***	0.51***	0.52***	0.52***	0.54***	0.55***
		(7.98)	(6.12)	(6.11)	(6.32)	(6.22)	(6.66)	(6.77)
	Sell	-0.58***	-0.35***	-0.37***	-0.38***	-0.40***	-0.40***	-0.40***
		(-6.37)	(-4.09)	(-4.28)	(-4.33)	(-4.46)	(-4.49)	(-4.58)
	Buy-Sell	1.26***	0.86***	0.87***	0.90***	0.92***	0.94***	0.95***
		(10.74)	(8.01)	(8.05)	(8.33)	(8.49)	(8.73)	(8.68)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Neutral	Intercept	1.05**	1.04**	1.04**	1.06**	1.05**	1.06**	1.05**
		(2.56)	(2.51)	(2.52)	(2.59)	(2.58)	(2.58)	(2.56)
	Buy	0.14	0.00	0.00	0.03	0.06	0.08	0.10
		(1.63)	(0.03)	(0.03)	(0.37)	(0.72)	(0.93)	(1.12)
	Sell	-0.60***	-0.49***	-0.50***	-0.52***	-0.51***	-0.49***	-0.48***
		(-6.64)	(-5.37)	(-5.67)	(-6.00)	(-5.84)	(-5.65)	(-5.56)
	Buy-Sell	0.74***	0.49***	0.50***	0.55***	0.57***	0.57***	0.57***
		(8.17)	(5.25)	(5.42)	(6.07)	(6.30)	(6.24)	(6.33)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Optimistic	Intercept	0.94**	0.92**	0.93**	0.94**	0.95**	0.95**	0.96**
		(2.26)	(2.22)	(2.25)	(2.26)	(2.29)	(2.29)	(2.31)
	Buy	0.21**	0.13	0.13	0.13	0.12	0.13	0.14
		(2.38)	(1.41)	(1.34)	(1.38)	(1.32)	(1.40)	(1.49)
	Sell	-0.36***	-0.20**	-0.20**	-0.23**	-0.24***	-0.26***	-0.28***
		(-4.52)	(-2.48)	(-2.33)	(-2.57)	(-2.76)	(-2.89)	(-3.10)
	Buy-Sell	0.57***	0.33***	0.32***	0.35***	0.37***	0.39***	0.42***
		(6.80)	(3.99)	(3.59)	(3.78)	(3.91)	(4.14)	(4.48)

Panel D: Recommendation revision - risk adjusted return

		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Pessimistic	Intercept	0.26**	0.25**	0.25**	0.25**	0.25**	0.26**	0.27**
		(2.55)	(2.43)	(2.29)	(2.29)	(2.34)	(2.35)	(2.43)
	Buy	0.67***	0.51***	0.50***	0.52***	0.51***	0.53***	0.53***
		(7.64)	(5.97)	(5.87)	(6.04)	(5.89)	(6.28)	(6.39)
	Sell	-0.55***	-0.33***	-0.35***	-0.38***	-0.40***	-0.41***	-0.41***
		(-6.04)	(-3.80)	(-4.06)	(-4.20)	(-4.37)	(-4.46)	(-4.56)
	Buy-Sell	1.22***	0.84***	0.85***	0.89***	0.91***	0.93***	0.94***
		(10.21)	(7.64)	(7.67)	(8.01)	(8.14)	(8.41)	(8.38)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Neutral	Intercept	0.47***	0.45***	0.46***	0.47***	0.47***	0.47***	0.47***
		(3.76)	(3.58)	(3.60)	(3.75)	(3.70)	(3.70)	(3.64)
	Buy	0.16*	0.03	0.03	0.06	0.09	0.11	0.13
		(1.86)	(0.35)	(0.33)	(0.68)	(1.05)	(1.28)	(1.43)
	Sell	-0.59***	-0.47***	-0.49***	-0.50***	-0.49***	-0.47***	-0.46***
		(-6.81)	(-5.42)	(-5.77)	(-6.06)	(-5.89)	(-5.68)	(-5.51)
	Buy-Sell	0.74***	0.50***	0.51***	0.56***	0.58***	0.58***	0.58***
		(8.49)	(5.55)	(5.72)	(6.48)	(6.81)	(6.73)	(6.76)
		K=1	k=3	k=6	k=9	k=12	k=18	k=24
Optimistic	Intercept	0.36***	0.34***	0.35***	0.35***	0.36***	0.37***	0.37***
		(3.10)	(2.88)	(2.83)	(2.83)	(2.87)	(2.91)	(2.96)
	Buy	0.20**	0.12	0.13	0.13	0.12	0.13	0.13
		(2.23)	(1.31)	(1.31)	(1.31)	(1.25)	(1.28)	(1.36)
	Sell	-0.36***	-0.19**	-0.17**	-0.20**	-0.21**	-0.23**	-0.25***
		(-4.45)	(-2.27)	(-2.01)	(-2.24)	(-2.42)	(-2.56)	(-2.71)
	Buy-Sell	0.56***	0.30***	0.29***	0.32***	0.33***	0.35***	0.38***
		(6.55)	(3.73)	(3.32)	(3.46)	(3.56)	(3.77)	(4.03)

Table 7: The analyst pessimism measure of Hugon and Muslu (2010)

We follow Hugon and Muslu (2010) and compute their conditional and relative measure of analyst pessimism as the estimate of $(\beta_0 + \beta_1)/\beta_1$ for the following regression model:

$$Rev_{i,j,t} = \alpha_{0,t} + \alpha_{1,j,t} * Badnews_{i,j,t} + \beta_{0,j,t} * avgRev_{i,j,t} + \beta_{1,j,t} * (avgRev_{i,j,t} * Badnews_{i,j,t}) + \epsilon_{i,j,t}$$

where $Rev_{i,j,t}$ is analyst i 's forecast revision, defined as her earnings forecast of stock j at time t minus the mean consensus forecast scaled by stock price; $avgRev_{i,j,t}$ is the average forecast revision of the two analysts surrounding analyst i ; $Badnews_{i,j,t}$ is a dummy variable taking the value of 1 if $avgRev_{i,j,t}$ is negative. $(\beta_0 + \beta_1)/\beta_0$ measures the degree of analyst i 's responsiveness to bad news versus good news. Regressions are performed annually for each analyst. Using the ex-ante analyst-year measure, we sort analysts into quintiles every quarter. The t -values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Replicate Table 5 of Hugon and Maslu (2010)

	1990:2006	1990:2006
	Model1	Model2
Intercept	0.0011*** (0.000)	0.0081*** (0.001)
Rev	0.6517*** (0.010)	2.6542*** (0.058)
Pessi	0.0002*** (0.000)	0.0004*** (0.000)
Rev*Pessi	0.0565*** (0.004)	0.0722*** (0.005)
absRev		0.0912*** (0.019)
Rev *absRev		-29.8946*** (0.305)
ME		-0.0012*** (0.000)
Rev *Me		-0.0272*** (0.005)
BM		0.0022*** (0.000)
Rev *BM		-0.3900*** (0.017)
Beta		0.0012*** (0.000)
Rev *Beta		0.2592*** (0.021)
N	934,022	667,838
R^2	0.0186	0.0451

Panel B: Calendar portfolio approach of Barber et al. (2001)

		Sell	Hold	Buy	Buy-Sell
<i>Alpha4f</i>	1=most pessimistic	-0.27	0.22	0.33	0.60***
		(-1.98)	(1.85)	(2.72)	(3.51)
	2	-0.29	0.05	0.31	0.60***
		(-2.48)	(0.43)	(2.41)	(4.53)
	3	-0.13	0.11	0.39	0.52***
		(-1.28)	(0.94)	(2.99)	(3.99)
	4	-0.10	0.31	0.34	0.44***
		(-0.91)	(2.79)	(3.06)	(4.86)
	5=least pessimistic	-0.03	0.22	0.26	0.29***
		(-0.25)	(1.75)	(2.22)	(3.14)
	1 - 5	-0.24	0.01	0.06	0.31*
		(-1.55)	-0.05	(0.61)	-1.72

Panel C: Calendar portfolio approach of Fang and Yasuda (2011)

		Sell	Buy	Buy-Sell
<i>Alpha4f</i>	1=most pessimistic	-2.93	2.32	5.25***
		(-13.42)	(14.21)	(22.88)
	2	-3.36	2.29	5.65***
		(-15.8)	(13.74)	(25.17)
	3	-3.01	2.13	5.14***
		(-13.88)	(13.16)	(23.12)
	4	-2.50	2.38	4.89***
		(-13.65)	(16)	(24)
	5=least pessimistic	-2.56	2.04	4.61***
		(-12.06)	(12.54)	(20.28)
	1 - 5	-0.35	0.27	0.63**
		(-1.55)	(1.44)	(2.29)

Table 8: Ex-ante forecast accuracy and subsequent profitability of stock recommendations

We use the absolute value of forecast distance away from consensus (*DIST*) as the basis for an ex-ante forecast accuracy measure. We sort analysts into quintiles based on the ex-ante measure of earnings forecast accuracy every quarter. The *t*-values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Calendar portfolio approach of Barber et al. (2001)

		Sell	Hold	Buy	Buy-Sell
<i>Alpha4f</i>	1=most accurate	-0.12 (-0.91)	0.35 (3.37)	0.52 (4.47)	0.64*** (5.23)
	2	-0.19 (-1.9)	0.24 (1.9)	0.30 (2.97)	0.50*** (4.56)
	3	-0.11 (-1.02)	0.26 (2.04)	0.22 (2.23)	0.33*** (3.02)
	4	-0.17 (-1.77)	0.01 (0.13)	0.39 (3.52)	0.56*** (5.48)
	5=least accurate	-0.20 (-1.94)	0.28 (2.51)	0.37 (3.2)	0.57*** (5.17)
	1 - 5	0.08 (0.64)	0.07 (0.46)	0.14 (1.33)	0.06 (0.46)

Panel B: Calendar portfolio approach of Fang and Yasuda (2011)

		Sell	Buy	Buy-Sell
<i>Alpha4f</i>	1=most accurate	-3.85 (-16.62)	2.30 (14.84)	6.15*** (25.85)
	2	-3.41 (-15.77)	2.40 (16.13)	5.81*** (26.57)
	3	-3.19 (-16.26)	2.32 (15.86)	5.51*** (26.45)
	4	-2.92 (-16.01)	2.27 (15.78)	5.19*** (26.42)
	5=least accurate	-2.24 (-13.48)	2.26 (16.2)	4.49*** (26.62)
	1 - 5	-1.61*** (-6.62)	0.04 (0.25)	1.65*** (6.24)

Figure 2: Cumulative abnormal return from day -1 to day 20 around the revision date

Graph A: Cumulative abnormal return by analyst type and recommendation type

Graph B: Cumulative percentage of relative profitability

Essay Two: Estimation Risk, Stock Returns and Momentum

Abstract

When prior information is of low quality, price change is often large on the earnings announcement date. We use the standard deviation of historical earnings announcement return as a proxy for stock estimation risk. We find that there is no significant premium to estimation risk in the U.S. stock market from 1978 to 2009, a result at odd with the theoretical prediction of Kumar, Sorescu, Boehmer and Danielsen (2008). In addition, we find that price and earnings momentum as well as forecast-revision drift is stronger among stocks with higher estimation risk, a result consistent with the notion that investors suffer from bias in processing information.

Keywords: estimation risk, earnings announcement, cross section of stock returns, momentum

JEL: G11 G12 G14

I. Introduction

Do investors know fully the return generating processes of investable assets? The answer is clearly no. Investors simply do not have the luxury of complete knowledge. All they can do is to make the best conjecture of return-risk parameters after processing all the investment related information. Traditional asset pricing models like CAPM generally impose an assumption of full information. Nevertheless, alternative theories that relax such an assumption would perhaps be closer to the reality.

We empirically study the effects of incomplete information on securities market with a measure based on earnings announcement returns. Intuitively, when the investment environment deviates from full information, corporate earnings announcements tend to generate large price changes. Analytical works of Holthausen and Verrecchia (1988) and Kim and Verrecchia (1991a, 1991b) prove such an intuition. Therefore, we are able to interpret the standard deviation of historical earnings announcement return as a measure of information quality (the variance of signals). Furthermore, in the context of a recent asset pricing model of Kumar, Sorescu, Boehmer and Danielsen (2008) (hereafter KSBD), this measure can be interpreted as a proxy for estimation risk.

KSBD relax the assumption of full information and develop a rational pricing model on estimation risk. In their model, investors do not have full information but have to learn about parameters of return generating processes from noisy signals. Investors learn from signals and update beliefs accordingly in a standard Bayesian fashion. As a result, the first and second moment estimates of stock returns depend on historical signals. Rational portfolio choices with such a return and risk assessment lead to an information-dependent conditional CAPM. The risk premium of any security has two components, one related to the intrinsic risk exposure and another to the estimation risk exposure. In the world of KSBD, the variance of signals is positively associated

with estimation risk. Therefore, we can further interpret the standard deviation of earnings announcement return as a proxy for estimation risk.

An important theoretical prediction made by KSBD remains untested, which is about the effect of the variance of signals on the cross section of stock returns in equilibrium. According to KSBD, stocks with less precise signals and hence greater estimation risk requires return premium. With the above-mentioned proxy for estimation risk, we can empirically test this prediction of KSBD.

Our second empirical prediction is about the role of estimation risk in momentum phenomenon. Daniel, Hirshleifer and Subrahmanyam (1998) propose a theory of over-confidence and investor attribution bias to explain the short-term momentum effect. Initially over-confidence produces an over-reaction and the subsequent attribution bias leads to a continued over-reaction. As a result, positive return correlation in the short term obtains. If investors suffer from behavioral biases when processing information and this is the root cause of momentum phenomenon, we hypothesize that momentum would be more pronounced when information is less reliable and the signal about stock valuation is less precise.

The following are the main findings and hence our contribution to the literature. First, we do not find that estimation risk carries significant premium in the U.S. stocks from Jan 1978 to Dec 2009 based on our empirical proxy. Monthly returns to stocks with the largest decile rank of estimation risk are 0.16% more than stocks with the smallest decile rank. Such a return differential is economically and statistically insignificant. Second, consistent with the notion that investors exhibit bias in processing information, greater momentum phenomena are among stocks with higher estimation risk. The momentum phenomena include price and earnings momentum as well as post analyst forecast revision drift.

Our study connects the finance and accounting literature on two fronts: information quality and stock momentum. Our paper immediately connects to KSBD. We do not find support for their

theoretical prediction of rational pricing of estimation risk, so provide more contents to theoretical debates on estimation risk. Recent works include Cvitanić et al (2006), Lambert, Leuz and Verrecchia (2007), Kan and Zhou (2007), Garlappi, Uppal and Wang (2007), Armstrong, Banerjee and Corona (2011).

Our study is close to Frankel and Litov (2009). They confirm the finding of Dichev and Tang (2009) that earning volatility affects earnings predictability, but show that earnings volatility does not predict stock returns. Our results contrast with those studies that show the cost of capital inversely relates to information quality (see, for example, Bhattacharya et al. (2003), Francis et al. (2004, 2005), Botosan et al. (2004), Aboody et al. (2005), and Hutton et al. (2009)).

On the stock momentum front, we find that momentum profitability relates to estimation risk. Therefore, our study connects to the momentum literature that identifies various firm characteristics as related to stock momentum strength. For example, the book-to-market ratio in Daniel and Titman (1999); institutional ownership in Hou and Moskowitz (2005); analyst coverage in Hong, Lim, and Stein (2000); turnover in Lee and Swaminathan(2000); idiosyncratic volatility and other firm characteristics about valuation uncertainty in Zhang (2006) and Jiang, Lee and Zhang (2005); return consistency in Grinblatt and Moskowitz (2004).

The remaining paper proceeds as follows. Section II introduces our proxy for stock estimation risk and two testable hypotheses on this proxy. Section III describes the sample selection. Section IV presents empirical results. Section V concludes the paper.

II. Research Design

In this section, we characterize earnings announcement returns with a simple one risky asset model of Holthausen and Verrecchia (1988). The characterization facilitates the introduction of our empirical proxy for estimation risk. Then, we introduce two testable hypotheses regarding

estimation risk based on earlier studies. First, estimation risk is important in asset pricing. High estimation risk stocks have greater returns than low estimation risk stocks. Second, estimation risk is important in explaining momentum profitability. High estimation risk stocks have stronger momentum effects than low estimation risk stocks.

IV.1 A simple model

When prior information is of low quality, earnings announcement returns tend to be volatile. The intuition is that the market is likely to be surprised by the announced earnings results. As a result, large stock price changes obtain. Such intuitions are analytically addressed by Holthausen and Verrecchia (1988) and Kim and Verrecchia (1991a, 1991b). We adapt a simple one risky asset model from Holthausen and Verrecchia (1988) to characterize stock price behavior around earnings announcement dates. The concept of estimation risk becomes evident after the model is illustrated.

Consider a market that consists of a single risky asset with one information release and a competitive risk neutral market maker. The market opens on day 0 and then trades continuously. On day T , an important piece of information about the asset value releases. Not long after the announcement, the risky asset is liquidated. On the trading days between day 0 and day T , even though there is no information release, investors still garner private signals about the asset value and trade on them. For simplicity, investors are homogeneous.

Figure 1: Time line for a simple model illustrating estimation risk

The liquidation value of this risky asset is random, denoted by $\tilde{u}$. At the inception of the market, investors have the prior belief that $\tilde{u} \sim N(m, v)$, which implies the stock price starts from

$$(1) \quad P_0 = E(\tilde{u}) = m.$$

For ease of exposition, the private signals received by investors during day 0 and day T is assumed to be a scalar and denoted by S , $S = \tilde{u} + \epsilon_s$ and $\epsilon_s \sim N(0, \delta)$.²² As investors trade on the signals, the stock price immediately before the announcement on day T is

$$(2) \quad P_- = E(\tilde{u}|S) = m + \frac{v}{v+\delta}(S - m).$$

Note that the day T announcement conveys a public signal, which can be denoted by $\tilde{y}$, $\tilde{y} = \tilde{u} + \epsilon_y$ and $\epsilon_y \sim N(0, p)$. It is assumed that ϵ_s , ϵ_y and $\tilde{u}$ are independent from each other. Immediately after the announcement, the stock price is

$$(3) \quad P_+ = E(\tilde{u}|S, \tilde{y}) = m + \frac{vp(S-m) + v\delta(\tilde{y}-m)}{(v+\delta)(\delta+p) - v^2}.$$

It can be shown that the price change owing to the announcement is

$$(4) \quad \tilde{\Delta} = P_+ - P_- = \frac{-v^2\delta(S-m) + v\delta(v+\delta)(\tilde{y}-m)}{(v+\delta)(v\delta + vp + \delta p)}.$$

The variability of price change is captured by the conditional variance of $\tilde{\Delta}$ on observing the pre-announcement stock price P_- ,

$$(5) \quad \text{Var}(\tilde{\Delta}|P_-) = \text{Var}(\tilde{\Delta}|S) = \text{var} \left[\frac{v\delta(\tilde{y}-m)}{(v\delta + vp + \delta p)} \right] = \frac{v^2\delta^2(v+p)}{(v\delta + vp + \delta p)^2}.$$

It can be shown that the above conditional variance is increasing in v and δ , and decreasing in p .²³ Intuitively, v and δ represent prior information about asset value before the announcement. As v and δ get larger, prior information deteriorates, less is known about the final liquidating

²²The signals can be easily generalized to a signal vector as in Kumar, Sorescu, Boehmer and Danielsen (2008).

²³The proof is available from us upon request.

value of the risky asset, and more can be learnt from the announcement, *ceteris paribus*. As a result, the price after announcement is less likely to be similar to the pre-announcement one, and a great change of stock price is expected.

The model can generalize to non-homogenous investors. Kim and Verrecchia (1991a, 1991b) show that the average precision of private signals matters when investors are diversely informed. When the average precision is low, the quality of pre-announcement information is low and the variability of price change is large.

IV.2 Estimation risk proxy

In the model, the precision of prior belief and the quality of intermediate private signals determine the size of market reaction to information release on the final date. Therefore, the variance of signals about the value of the firm can be captured by the volatility of price change on announcement dates. Moreover, because the variance of signals positively relates to estimation risk in the world of KSBD, which we discuss in the next subsection, earnings announcement returns can be used to construct an empirical proxy for estimation risk.

For each stock in month t we collect earnings announcement returns (denoted as EAR) in the last 20 quarters. We compute the standard deviation of those earnings announcement returns (denoted as $DEAR$) and use it as our empirical proxy for estimation risk. Each earnings announcement return is a three-day cumulative abnormal return from the market-return adjusted model, where CRSP value-weighted market index is used as the market return. Figure 2 explains our proxy for estimation risk.

Figure 2: Time line in constructing our proxy for estimation risk

In robustness tests, we try two other ways of computing the proxy for estimation risk. One is to take the standard deviation of earnings announcement returns in the last 16 quarters instead of 20 quarters. The other one is to use the moving average of absolute value of earnings announcement returns in the last 20 quarters.

In fact, empirical measures derived from the earnings surprises can be found in earlier studies. Chordia, Huh and Subrahmanyam (2007) define earnings surprise as current earnings minus earnings from four quarters ago and use the absolute values of earnings surprises as the proxy for uncertainty about fundamental values. Kim (2006) fits the time series of quarterly earnings with an AR(1) model and the standard deviation of residuals is used as earnings information quality. Our empirical proxy is different from theirs in that only the market return is used and there are no problems associated with model fitting.

Note that price impact of earnings disclosures can be interpreted in a different manner. Hautsch and Hess (2007) suggest that price impact could proxy for the precision of released information itself. However, as argued by Berkman et al. (2009), earnings announcement is an event that resolves uncertainty. In this sense, price impact is about the precision of pre-event signals.

IV.3 Hypothesis development

KSBD develop a rational equilibrium model of estimation risk, where an information-dependent conditional CAPM holds. Asset risk premium has two components: the risk premium due to the asset's intrinsic systematic risk, and the risk premium due to the asset's sensitivity to the market estimation risk factor. The variance of signals has important ramifications in the cross section of stock returns. According to Proposition 2 of KSBD, if the signal of one security second-order stochastically dominates that of another security, this security is subject to less estimation risk, and

demands less return. The total required return of this security is therefore lower. Let ω_{it} be the sample variance of signals for firm i at the beginning of time period t , controlling for all other risk factors, the theory of KSBD suggests that the expected return of stock i should be increasing in ω_{it} . In the form of expected-return specification,

$$(6) \quad E(r_{it}) = \bar{r}_f + \bar{\beta}_i * \bar{R}_M + \eta_i * \omega_{it},$$

KSBD impose that $\eta_i > 0$. Equation (6) has not been tested by KSBD and is identified as the first testable hypothesis in our study.

Hypothesis 1: Estimation risk measured by *DEAR* is a determinant of stock returns. High *DEAR* stocks have greater returns than low *DEAR* stocks.

It is useful to illustrate the basic model setup of KSBD to understand why estimation risk should matter in stock pricing. This is a one-period economy. A representative investor is risk averse with the exponential utility function and faces with the choice of J risky assets and one riskless asset. The final payoffs to risky assets are random with the mean of $\mu = (\mu_1, \mu_2 \dots \mu_J)$ and the variance, or covariance matrix, of $\Sigma = [\sigma_{i,j}]$. The investor does not observe μ and has to learn from signals, $S_{i,t} = \mu_i + \epsilon_{i,t}, i = 1 \dots J; t = 1, 2, \dots n$. It follows that the likelihood function for signals is $f(S|\mu, \Gamma)$, where Γ is the precision matrix of signals.

It is important to note that KSBD assume the investor is not certain about the precision of information (Γ). Because of this important assumption, when the prior belief about (μ, Γ) belongs to the Normal-Wishart distribution family, the posterior belief about the two parameters (μ, Γ) are analytically derived. The mean of updated μ is a function of the sample mean of S and the variance of updated μ is a function of the sample variance of S . Thus, the risk return tradeoff relationship in the investors' portfolio is a function of signals, S . The risk perceived by the investor is then a function of signals. As a result, we have a CAPM conditional on S . Note that if

the investor has perfect knowledge about the quality of information (Γ), the updated μ follows a normal distribution with a definite variance number. Under this specification, the variance of signals will not be a determinant of stock returns.

Hypothesis 1 is derived from the rational pricing framework of KSBD where investors' belief updating is in the standard Bayesian fashion. A bounded rationality framework of Epstein and Schneider (2008) arrives at similar conclusions. Their framework assumes that investors update beliefs as if multiple likelihoods are possible. Investors act as if they take a worst-case assessment of signal quality. They dislike assets for which information quality is poor. Therefore, investors require ambiguity premium, which depress today's stock price. In our empirical study, we do not seek to distinguish these two theoretical frameworks.

Our second hypothesis pertains to stock momentum phenomena. Jegadeesh and Titman (1993) documents the existence of price momentum effect. A hedge portfolio that longs past six-month winners stocks in the top decile and shorts past six-month losers stocks in the bottom decile delivers about 1% per month in the next six months. Chan, Jegadeesh and Lakonishok (1996) extend the scope of momentum strategies and draw a broader picture in which stock market responds gradually to new information. Past return, past earnings surprise and analyst forecast revision in the past each predicts large drift in future returns even after controlling for the others.

Analytically, De Long et al (1991) suggest that stock momentum might be a manifestation of continued over-reaction by proposing a positive-feedback-trader model. Bikchandani et al. (1992) suggest that precision of signal affects the likelihood of a cascade in price movement. When each individual receives a noisy signal, it is often optimal to follow the behavior of the preceding traders without regard to his or her own information. Daniel, Hirshleifer and Subrahmanyam (1998) propose a theory of over-confidence and investor attribution bias to explain stock momentum. The investor's confidence grows when public information is in agreement with his

own information, and does not fall by an equal amount when public information is contradictory. Such behavioral bias causes prices initially overreact to news about fundamentals, then continue to overreact further for another period. This explains positive short-lag autocorrelations in stock returns.

If behavioral biases and psychological predicaments in processing information are the causes of stock momentum, we expect stronger momentum when the signal about stock valuation is less precise. Psychological studies show that investors are prone to overconfidence in situations where feedback on their information or decision is slow or inconclusive.²⁴ Hirshleifer (2001) also posits that lack of accurate feedback about stock values leaves more room for psychological biases. Therefore, we have the second empirical hypothesis in its alternative form.

Hypothesis 2: Momentum effects, including price momentum, earnings momentum and analyst forecast revision drift, are stronger among high DEAR stocks than low DEAR stocks.

In fact, there are other competing momentum theories. Barberis, Shleifer and Vishny (1998) assume that a representative investor suffers from a pessimism bias, and therefore does not update his beliefs sufficiently upon new public information. Hong and Stein (1999) assume that firm-specific information diffuses gradually across the investors, which is empirically confirmed in Hong, Lim and Stein (2000). Grinblatt and Han (2004) put forward an anchoring bias theory to explain short term return correlations. In empirical studies, George and Hwang (2004) support an anchoring story. Conrad and Kaul (1998) find that momentum profits are due to differences in expected return, while Jegadeesh and Titman (2002) suggest otherwise. Our empirical tests that follow Jegadeesh and Titman (2002) in the later section support the prolonged over-reaction theory as reversal seems stronger for high estimation risk stocks.

²⁴References can be found in Hirshleifer (2001).

III. Sample formation

Our sample begins from Jan 1978 and ends in Dec 2009. NASDAQ firms are only available in CRSP after 1973 and the computation of our proxy for estimation risk requires earnings announcement returns in the prior 20 quarters. Moreover, records of earnings announcement dates are only available from COMPUSTAT after the fourth quarter of 1971. So the sample period we choose is almost the largest possible.

We follow the sample selection procedures of Fama and French (1992, 1993) to determine the cross section of stocks in our sample for the above period. In addition, we exclude low priced stocks. Speculative trading and liquidity problems plague these stocks. Excluding them is to ensure that our results are free from these problems. Therefore, a stock must satisfy the following criteria to be included in our final sample.

1. The stock is a common stock with a share code of 10 or 11 in CRSP.
2. The stock has at least 5 years records in CRSP for market beta estimation.
3. The company has records for the previous fiscal year in COMPUSTAT.
4. The company has non-negative book values.
5. The stock price is above \$5²⁵.

Because of the above procedures, some firm characteristics obtain. *ME* is the market value of firm equity, defined as the closing stock price multiplied by the total number of shares outstanding in the last month. *BM* is the book to market equity ratio. The book value of equity is sourced from financial statement of last fiscal year. *BETA* is the post-ranking market beta calculated in the same way as in Fama and French (1992). Specifically, at the beginning of each month, market betas for individual stocks are firstly computed. Then they are used together with the market size as two sorting variables to form 100 equally weighted stock portfolios. The market beta of individual

²⁵This is to exclude penny stocks. We require stocks price to be greater than \$5 at the beginning of the month.

stocks in each of the 100 portfolios will then assume the portfolio level beta. The computation procedure repeats every month and monthly market beta of each stock obtains.

We also compute various other variables for sample stocks subject to data availability. *EAR* is the most recent quarterly earnings announcement return, defined as a three-day abnormal return from the market-return adjusted model around the announcement date. *VOLT* is total return volatility, defined as standard deviation of stock returns of the trailing 12 months that ends at the beginning of last month. *IVOL* is the idiosyncratic volatility relative to the Fama-French three-factor model, as defined in Ang, Hodrick, Xing and Zhang (2006, 2010). Specifically for each stock-month, daily stock returns are regressed on daily factor returns and daily residuals out of each stock-month regression are collected. The standard deviation of daily regression residuals multiplied by the square root of the number of trading days in that month is the idiosyncratic volatility for that stock-month.²⁶ *NSKEW* is the negative skewness of stock returns as in Chen, Hong and Stein (2001) based on the daily return in the previous quarters.²⁷

The remaining variables are as follows. *IO* is the institutional ownership from Thomson Financial 13F database. Gompers and Metrick (2001) show that institutional ownership predicts a positive three-month future return.²⁸ To ensure price validity, we replace the stock price in 13F with that in the CRSP database. *ANALYST* is the number of analysts from IBES database. Stocks not covered by analysts are assumed to have zero analyst coverage. *TURN* is the average turnover and *CVTURN* is the coefficient of variation of monthly turnovers in the past six months, defined as in Chordia, Subrahmanyam and Anshuman (2001). *FDISP* is the analyst forecast dispersion, defined as in Diether, Malloy, and Scherbina (2002). To analyze the analyst forecast revision drift, we

²⁶Noteworthy is that *VOLT* is the total return volatility using the 12 trailing monthly returns and *IVOL* is the idiosyncratic volatility computed using daily returns of each month. So *VOLT* is not necessarily equal to *IVOL* plus market volatility.

²⁷In Chen, Hong and Stein (2001), the stock skewness measure is based on daily returns within every six-month period.

²⁸Yan and Zhang (2009) confirm the finding and further documents the relation is caused by short-term institutional ownership.

compute the average revision in the past three months, denoted as *REV*. *EP* is the earnings to price ratio. *DEPS* is to capture volatility of fundamentals. It is defined as the standard deviation of *EP* ratios on each earnings announcement date in the last 20 quarters. *ACCR* is the total accruals to total assets ratio. *CAPEX* is total capital expenditures as a proportion of total assets. *SGRT* is the sales growth rate, defined in gross terms $(1+g)$. *PIN* is the probability of informed trading measure from Easley, O'Hara and Hvidkjaer (2002). We provide detailed illustrations on how the variables are sourced and computed in the appendix.

In order to avoid potential database errors and also contain the adverse outlier influence in regression analysis, we winsorize the sample on the variables *ME*, *BM*, *DEAR*, *VOLT*, *IVOL*, *NSKEW*, *TURN*, *CVTURN*, *AMIHU*, *SGRT*, *EP*, *DEPS*, *ACCR*, *CAPEX*, *FDISP* and *REV* at both ends of 0.5%. That is, the smallest and largest 0.5% of these variables are set equal to the next smallest or largest values.²⁹

Table 1 is about here.

Panel A of Table 1 presents summary statistics for our sample from 1978 to 2009. Note that the total number of observations (stock-month) is 1,153,213. This is plausible compared with what Fu (2009) reports: 1,721,356 stocks from 1965 to 2006 with valid beta estimates. The mean and median beta of our sample is respectively 1.26 and 1.22, whereas for his sample is respectively 1.22 and 1.17.

Note that the total number of observations with valid *DEAR* is 1,027,921, less than that obtained with the Fama and French (1992) procedure. This is because computation of the measure *DEAR* has additional restrictions on the dataset. The mean of *DEAR* is 6.13% while the median is 5.26%. This suggests that the magnitude of earnings announcement return is on average 5 to 6 percent. This number is in line with standard deviation of total observations of *EAR*, which is 7.26%.

²⁹Our results are not sensitive to the exclusion of over 300% extreme returns from the sample as in Fu (2009).

The other variables are selectively described as follows. The mean total volatility (*VOLT*) is around 11.4% while the mean idiosyncratic volatility (*IVOL*) is 9.88%. The idiosyncratic volatility statistics is comparable to what is reported in Fu (2009).³⁰ The institutional ownership is available only after 1980, with the mean of 38.39% and standard deviation of 28.67%. Analyst coverage is available in IBES from 1976. IBES only covers about half of the total month-stock observations, so only 659,054 observations have valid *FDISP*.³¹ The mean *TURN* is about 0.09, suggesting around 9% of shares change hand on average. The stock illiquidity measure *AMIHUD* has a median of 1.2, suggesting that one million dollar volume induces a 1.2% of price change. The mean (median) of earnings to price ratio (*EP*) is 4% (4%). *ACCR* has a mean of 3.63% but with a large dispersion, its standard deviation being 12.69%. *CAPEX* is available only after March 1981. The negative value of this variable is likely caused by database errors. *SGRT* is the total sales growth rate, a mean of 1.16 meaning an average growth rate of 16%.

We calculate times series average of cross sectional correlations among variables but do not tabulate them. We regard an absolute value of 0.2 as the threshold level of significant correlations, and find that *DEAR* is positively associated with *BETA*, *VOLT*, *IVOL*, *AMIHUD*, *TURN*, *DEPS*, and *PIN*. This indicates that high volatility stocks generally have high estimation risk, whether such volatility is systematic or idiosyncratic. Stocks with large turnover, earnings volatility in the past, and information asymmetry have high estimation risk. We find that *DEAR* is negatively associated with *ANALYST*, which suggests that financial analyst coverage lead to low estimation risk.

³⁰Fu (2009) reports higher mean and standard deviation than us. This is likely because we compute summary statistics after winsorizing the data. The conjecture is supported by the fact the median value is close to his. When we compute summary statistics before winsorizing the data, the statistics is equal to his.

³¹We replace missing values of analyst coverage with zeros so that the total number of observations for this variable is the same with that for *BETA*. Note, however, the missing values of forecast dispersion *FDISP* are not set equal to zeros for obvious economic reasons.

IV. Empirical Results

In this section, we examine whether estimation risk is an important determinant of stock returns. In addition, we examine whether estimation risk is positively associated with stock momentum effects. We then perform some robustness tests, including the sub-period analysis and two alternative ways of computing the estimation risk proxy.

IV.1 Pricing of estimation risk

This subsection is to examine the first hypothesis of our paper: whether high estimation risk stocks earn higher returns. As many studies in the literature, we present both the sort and regression results. We begin by sorting stocks into 10 portfolios by *DEAR* each month from Jan 1978 to Dec 2009. *DEAR* portfolios are rebalanced every month. We collect one-month ahead returns of all the individual stocks and compute the portfolio return for each monthly *DEAR* portfolio.

Table 2 is about here.

Panel A of Table 2 gives results when stocks are equally weighted in the portfolios. Column 1 reports the average raw stock returns to *DEAR* portfolios. The smallest decile stocks, which have the lowest estimation risk, earn 1.11% per month on average from Jan 1978 to Dec 2009. The largest decile stocks with the highest estimation risk earn an average of 1.27% per month in the same period. The return spread between the largest and smallest deciles is annualized to be 1.92 percent, which is not economically significant. The *t* test on the two monthly return series yields a *t*-statistics of 0.47. Note also that among other groups of stocks, though high *DEAR* stocks generally have larger returns, the return difference is not significant.

We further examine if *DEAR* relates to future returns after risk adjustments. To account for risk exposures, we run time series regression of monthly *DEAR* portfolio returns against systematic risk factors. The alphas out of regressions are stock returns that have been adjusted for risk, and

will then be compared among *DEAR* portfolios. For example, we use the Carhart (1997) four-factor model and run the following regression for each *DEAR* portfolio,

$$(7) \quad (R_p - r_f)_t = \alpha_p + b_p \cdot MKT_t + s_p \cdot SMB_t + h_p \cdot HML_t + u_p \cdot UMD_t + \varepsilon_t,$$

where $(R_p - r_f)_t$ is the excess return of *DEAR* portfolio p over risk-free interest rate in month t from 1978 to 2009; MKT_t , SMB_t , and UMD_t are the market factor, the size factor, the book-to-market factor and the momentum factor, respectively. The estimated $\widehat{\alpha}_p$ is the Carhart four-factor alpha, denoted as $Alpha4f_p$. If we drop the momentum factor from Equation (9), we have the Fama-French three-factor model (Fama and French, 1993) alpha denoted by $Alpha3f_p$. If only the market factor is in the model, we have the market model alpha, denoted as $CAPM$. Column 2 to 4 of Panel A report average returns after risk adjustment for *DEAR* portfolios. Again, we do not find *DEAR* significantly relates to stock returns

We measure abnormal stock returns based on firm characteristics following Daniel, Grinblatt, Titman, and Wermers (1997). The characteristics based benchmark returns and stock assignment data are sourced from the website of Russ Wermers.³² Those data are based on Wermers (2004), which is a refined version of Daniel et al. (1997). Column 5 of Panel A reports average abnormal stock returns adjusted for stock characteristics. Again, we do not find that returns are positively associated with *DEAR* ranks.

We restrict sample stocks to NYSE listed stocks and repeat the sorting procedure. This is to make sure the finding is not unique to certain exchange characteristics. When raw returns are used as in Column 6 of Panel A, we find the top and bottom return difference is 0.52% per month, both statistically and economically significant. However, when we use the Fama-French three factor-model to adjust for risk exposures in Column 7 of Panel A, the return difference disappears.

³²The webpage is found on the following website:
<http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm>

We present results when stock portfolios are value weighted in Panel B. They are similar to Panel A, therefore, our finding is robust to the portfolio weighting scheme. In Panel C, we independently sort stocks into five groups by *DEAR* and three groups by the other firm characteristic (*ME*, *BM* or *IVOL*). Double sorting results in 15 monthly portfolios. We find that *DEAR* is not related to stock returns by controlling for firm size (*ME*) or *BM*. However, by controlling for *IVOL*, we find that high *DEAR* stocks generally have larger returns than low *DEAR* stocks within the same *IVOL* tercile. The return difference is significant within the middle *IVOL* tercile. In light of this finding, *DEAR* may well capture different risk from *IVOL* even though their correlation is high (0.433).

We continue with regression analysis. As many empirical asset pricing studies, we adopt the Fama-Macbeth (1973) regression framework. Each month a cross-sectional regression is performed of stock return on *DEAR* and the control variables. The time series of monthly parameter estimates are then used to derive the Fama-Macbeth parameter estimates and *t* values. For example, we specify the monthly regression model as

$$(8) \quad Ret_i = a + b \cdot DEAR_i + c \cdot BETA_i + c \cdot ME_i + c \cdot BM_i + d \cdot other_control_i + \varepsilon_i,$$

where *other_control_i* contains a list of control variable choice as described in Section II.

Table 3 is about here.

Table 3 reports results of regression analysis. Note that log *BM* and log *ME* are used instead of the original variables in the regression. Column 1 repeats the analysis of Fama and French (1992) for our sample stocks where only beta, firm size and *BM* are explanatory variables in the model. We find that *BM* are significantly priced. Column 2 is the base model, where *DEAR* is firstly used. We find that *DEAR* is positively but not significantly associated with stock return.

We add *IVOL* to the base model in Column 2.³³ We find that *DEAR* is significantly and positively related to stock return. *IVOL* is significantly and negatively related to stock return, which is consistent with Ang et al. (2006) and Fu (2009). The control of *IVOL* makes *DEAR* significant in regressions confirms the prior double-sorting results in Table 2.³⁴

In Column 4, we add *FDISP* to the base model. We find that *FDISP* is significantly and negatively related to stock return. This is consistent with Diether, Malloy and Scherbina (2002). We find *DEAR* positively but not significantly relates to stock return. Note that *FDISP* is non-missing only for those stocks that are covered by IBES. So the number of observation involved in Column 4 is around half of Column 2.³⁵

In Column 5, we add the *PIN* measure of Easley, O'Hara and Hvidkjær (2002) to the base model. The *PIN* estimates downloaded from Hvidkjær's website are only available from 1983 to 2001. We do not confirm their conclusion that *PIN* is positively priced.³⁶ We find that *DEAR* is negatively associated with stock returns for the subset of stocks with valid *PIN* estimates.³⁷ The negative association is not statistically significant though.

In Column 6, we adds more control variables to the base model, including stock illiquidity of Amihud (2002), analyst coverage, earnings to price ratio (*EP*), standard deviation of *EP*, the accounting accrual and the sales growth rate. *COVERAGE* is the log of one plus the number of analysts. Note that all these variables are available from 1978. Therefore, the model specification

³³*VOLT* and *IVOL* is closely related with a correlation coefficient of 0.5. Therefore, we only report results using *IVOL* while *VOLT* related results are very much similar.

³⁴Ang et al. (2006) shows that *IVOL* is negatively related to stock return and believe it to be a financial anomaly since Merton (1987) predicts idiosyncratic risk premium. Fu (2009), on the other hand, shows that *IVOL* is priced because of return reversals of a small subset of stocks that have experienced huge price run-up and assumed high idiosyncratic volatility recently. Bali and Cakici (2008) find that the relation between idiosyncratic risk and stock return as documented by Ang et al (2006) is not robust to the price screen.

³⁵Hong, Lim and Stein (2000) as well as Diether, Malloy and Scherbina (2002) discuss that IBES coverage tends towards big firms.

³⁶We replicate the results of Easley et al. (2002) for their sample stocks from 1983 to 1998. In their Table VI, the *t*-value of *PIN* is 2.5 and we find is 2.7. Note, however, with a few more years added and the NYSE stock sample is from 1983 to 2001, the result does not hold and *PIN* is no longer significant.

³⁷Yan (2009) document that the joint market share of stocks with valid *PIN* estimates is only 52% of the entire market in 2001.

in this column allows for the maximum number of observations in the regression. We find that *DEAR* is positively but insignificantly related to stock return. We do not find that the illiquidity measure of Amihud (2002) is positively related to stock returns for our sample stocks.³⁸ We repeat the well-documented accrual anomaly that *ACCR* is significantly and negatively related to returns.

Compared with Column 6, Column 7 adds three additional variables, negative skewness of stock returns (*NSKEW*) of Chen, Hong and Stein (2001), institutional ownership (*IO*) and capital expenditure (*CAPEX*). The skewness measure is negated, meaning “prone to crash”. Kothari, Shu and Wysocki (2008) find that managers disclose good news timely but cumulate bad news. The market reactions to bad earnings news are therefore much stronger. To address the concern that *DEAR* may simply pick up the fact that investors dislike bad disclosure behaviors, we control for such a skewness measure. *IO* is only available after 1980 and *CAPEX* after 1981. The number of observation involved is hence smaller than that of Column 6. We again find that the *DEAR* coefficient is not significantly positive. We confirm the result of Fu (2009) about *CVTURN*, which is negatively related to stock return. We find *CAPEX* is inversely related to return, consistent with the well documented negative expected return-investment relation (see, e.g., Li and Zhang (2010)). We do not find that *IO* is positively related to one-month ahead stock return.³⁹

Compared with in Column 7, in Column 8 we replace the liquidity measure of Amihud (2002) with the alternative liquidity measures, *TURN* and *CVTURN*, from Chordia, Subrahmanyam and Anshuman (2001). We also drop the skewness measure but add the log price. We find that *DEAR* is significantly and positively related to returns in this model specification.

Overall, Table 3 shows that *DEAR* does not significantly predict stock returns. The return predictability is not robust to variations in the model specification or the sample of stocks used.

³⁸When we restrict the stocks to NYSE and the sample years from 1981 to 1997 without the control of log BM, we do find similar findings to Amihud (2002) with a similar t-value.

³⁹We do find positive relations between *IO* and 3-month or 12-month ahead stock return in quarterly regressions as in Gompers and Metrick (2001).

Taken together with Table 2, we conclude that high *DEAR* stocks are not significantly associated with high stock returns. Therefore, we do not find evidence in favor of the theoretical prediction of KSBD.

IV.2 Momentum and estimation risk

In this subsection, we test the second hypothesis of our paper. Estimation risk is a function of signal variance and therefore is associated with momentum effects. We expect greater momentum effects among high estimation risk firms. Again, we seek to provide both the sort and regression evidence.

Following Chan, Jegadeesh and Lakonishok (1996), we identify three types of momentum phenomenon. The first type of momentum is price momentum. Stock price continues in the direction of past price change. In a horizon from six to twelve months, Jegadeesh and Titman (1993) document that winner stocks continue to beat loser stocks. The second type of momentum is earnings momentum. Stock prices drift in the direction of earnings surprises. Positive earnings surprise stocks realize positive future stock return, while negative earnings surprise stocks deliver negative returns. The third type of momentum is analyst forecast revision drift. If the earnings forecast goes up, positive future stock returns are expected, and negative vice versa.

We use a six-month holding period return as the metric for price and earnings momentum as well as analyst revision drift. To ensure that return predictability is not caused by extreme returns, we delete any six-month return greater than 10. For each of the three types of momentum phenomenon, we identify one ranking variable as in Chan, Jegadeesh and Lakonishok (1996). The ranking variable for price momentum is the accumulative stock return in the last six months, denoted as *PRET*. Following the literature, we skip by one month to avoid return reversals. In other words, the six-month period for past return accumulation is from month -7 to month -2 when current month is month 0. For earnings momentum, the ranking variable is the most recent

earnings announcement return, denoted as *EAR*. And finally for analyst forecast revision drift, the ranking variable is the average revision in the past three months, denoted as *REV*.⁴⁰

We begin with two-way sorts. Following Zhang (2005), in each month we firstly sort stocks into quintiles by *DEAR*. Then within each *DEAR* quintile of stocks, we further sort stocks into quintiles by the ranking variable of momentum. Equally weighted six-month holding period return is computed for each portfolio.⁴¹ And the results are tabulated in Table 4.

Table 4 is about here.

Panel A of Table 4 presents the differential price momentum that estimation risk can produce. In Panel A, we find that within each quintile of *DEAR* portfolios, future return line up with *PRET* ranks, confirming the price momentum effect. Such a momentum effect is stronger among high estimation risk stocks. The price momentum effect captured by the return spread between the largest and smallest quintile of *PRET* stocks is only 2.06% for the lowest estimation risk stocks. However, for the highest quintile of *DEAR* stocks, price momentum effect almost doubles to 6.29%. The difference in the price momentum effects among the smallest *DEAR* quintile and largest quintile stocks is 4.23% and such difference is significant at the 1% level.

Panel B presents the differential earning momentum associated with estimation risk. We find that within each quintile of *DEAR* stocks, future return is associated with earnings surprise quintile ranks. The return spread owing to earnings momentum ranges from 0.89% to 4.89%. Note that the return spread within each quintile of *DAER* stocks owing to earnings momentum is smaller than that produced by price momentum. This actually confirms findings in Chan, Jegadeesh and Lakonishok (1996) that the spreads in returns associated with the earnings momentum

⁴⁰Consistent with the definition of forecast dispersion, we require the number of analysts per stock to be equal or greater than 3. Without such a requirement, the number of sample stocks increases by about 200,000 and the results are qualitatively the same. Also, the result is similar when the analyst revision drift is taken over the past six months instead of 6 months.

⁴¹Sagi and Seasholes (2007) offer discussions on why sequential double sorting is preferred over independent double sorting.

strategies tend to be smaller than that with the price momentum strategy. From this panel, we find the differential earnings momentum that is produced by estimation risk. Such a finding is not a repeated exercise of Panel A as Chordia and Shivakumar (2006) suggest earnings momentum is perhaps more important. They offer empirical evidence different from Chan, Jegadeesh and Lakonishok (1996) and conclude that price momentum can be captured by systematic component of earnings momentum. Note in Panel B, the difference in the earnings momentum effect between the largest and smallest quintile of DEAR stocks is 4%, with stronger statistical significance than what is reported in Panel A.

Panel C of Table 4 presents differential analyst forecast revision drift in the context of estimation risk. Within each *DEAR* quintile, future stocks return generally increases with forecast revision quintile ranks. Like price and momentum earnings, revision drift is related to estimation risk. The analyst revision drift is measured by the return difference between top and bottom revision quintile within each *DEAR* quintile. We find that the revision drift is only 2.62% for low estimation risk stocks but 6% for high estimation risk stocks. Such difference is comparable to the price and earnings momentum in terms of economic magnitude and statistical significance. This finding is important, as the sample of stocks involved in revision drift is a little more than half of that in the other two phenomena of momentum.

We continue with regression analysis on the differential momentum effects associated with estimation risk. We interact DEAR with the ranking variable for each momentum phenomenon. We expect to see significant and positive interaction effects. In regressions, the dependent variable is a six-month holding period return. The independent variables are the momentum variables, the interaction term plus all the explanatory variables in Column 6 of Table 3.

Table 5 is about here.

Table 5 presents regression evidence on differential momentum effects produced by estimation risk. Panel A tabulates results on price momentum. In Row 1, both *DEAR* and *PRET* coefficients are significantly positive when there is no interaction term. This shows the return predictability of estimation risk over a six-month period. This also confirms the well-documented price momentum. When the interaction between *DEAR* and *PRET* is introduced, it is found to be significantly positive from Row 2 to Row 4 with different controls. In particular, the interaction term of *PRET* and *IVOL* is controlled. This panel shows that price momentum effect is more significant when stocks subject to more estimation risk. Panel B tabulates results on earnings momentum, and Panel C on revision drift. The findings are similar. We find both earnings momentum and analyst drift are positively associated with estimation risk.

IV.3 Reversal indication

We follow Jagadeesh and Titman (2002) and accumulate return for each momentum portfolio beyond a six-month holding period. The analysis of this subsection sheds light on the underlying mechanism that causes momentum. In developing our second hypothesis, the theory of self-attribution bias of Daniel et al (1998) is used. This theory predicts that continued over-reaction produces the short term momentum phenomenon. Since behavioral bias ought to be more severe when estimation risk is high, we hypothesize that high *DEAR* stocks enjoy high momentum profits. If the underlying cause is indeed as described by Daniel et al (1998), we ought to see greater reversal of stock return for the momentum strategy portfolio within high *DEAR* stocks.

We look at the hedge portfolios of momentum or drift within the top and bottom quintile of *DEAR* stocks in Table 4. The hedge portfolio is a portfolio of stocks that are long in the largest quintile of the momentum variable and short in the smallest quintile of the momentum variable. For example, the hedge portfolio of price momentum is the fifth quintile of *PRET* stocks minus the first quintile of *PRET* stocks. The results are in Table 6.

Table 6 is about here.

Table 6 is continuation of Table 4. Note that the t -statistics is computed based on the time series of monthly portfolio returns from Jan 1978 and Dec 2009. From Panel A of Table 6, we see that profits of price momentum strategy are significantly reversed in high *DEAR* stocks after six months. Panel C of Table 6 also suggests that analyst revision drift is a result of continued over-reaction as greater reversals are observed for stocks with high *DEAR*. In Panel B, however, the return reversal is not obvious for the earning momentum. This does not suggest that earnings momentum is due to continued over-reaction but confirms Bernard and Thomas (1989) that post earnings announcement drift is due to investors' under-reaction. Investors do not seem to appreciate the implication of current earnings for future earnings.

IV.4 Robustness tests

In this subsection, we take the preceding major findings to a series of robustness tests. Firstly, we conduct sub-period analysis and divide the sample into two sub-periods, 1978-1994 and 1995-2009. Secondly, we use two alternative ways of computing the empirical proxy for estimation risk. For both robustness tests, we examine the first and second hypothesis of this paper. That is, we show if there is the pricing effect and the differential momentum effects associated with estimation risk. Test results are in Table 7.

Table 7 is about here.

Panel A of Table 7 presents the sub-period analysis. The regression model in Column 6 of Table 3 is used to test the pricing effect of estimation risk. We find that *DEAR* does not significantly predict stock returns in both sub-periods. The model from Row 4 of each panel in Table 4 is used to test differential momentum effects produced by estimation risk. We find that *DEAR* is significantly associated with greater price momentum in the first half period, and not significantly

in the second half period. *DEAR* significantly predicts greater earnings momentum effects in both periods. *DEAR* significantly predicts greater analyst forecast revision drift in both periods.

Panel B of Table 7 shows robustness tests with two alternative ways of computing the estimation risk proxy. The first way is to use the average absolute value of earnings announcement returns in the last 20 quarters, denoted as “*abs*”.⁴² The second way is to use the standard deviation of earnings announcement returns in the last 16 quarters, denoted as “*16 qtr*”. We find that these two new proxies do not significantly predict higher return, but are significantly associated with greater momentum effects. Therefore, our finding on estimation risk is not sensitive to the choice of proxies.

We conduct one additional robustness test but do not tabulate results for brevity. One is related to the well-known January effects. Kim (2006) constructs a common risk factor on information uncertainty associated with earnings volatility and find that cross sectional stock returns in January can be explained by the additional risk factor. His study suggests that large returns in January might be a risk premium for taking information uncertainty risk regarding corporate earnings. We conduct analysis respectively on the January and non-January sub-samples. Using the multivariate regression framework of Table 3, we find that *DEAR* is significantly related to stock returns in January months in all the model specifications, which supports Kim (2006). Portfolio analysis finds that stocks of the highest *DEAR* decile rank earn significantly higher returns than stocks with the lowest *DEAR* rank in January months. The return spread is a monthly 237 basis points. However, there is no significant association in non-January months, both in the portfolio and regression analysis.

⁴²Hutton, Marcus and Tehranian (2009) present a proxy of firm opaqueness using moving average of accrual in the last three years.

V. Conclusion

Guided by analytical studies of Holthausen and Verrecchia (1988), Kim and Verrecchia (1991a, 1991b), and KSBD, we interpret the standard deviation of earnings announcement returns as an empirical proxy for stock estimation risk. We introduce two hypotheses regarding estimation risk and test them on this proxy. Specifically, we analyze the impact of estimation risk on the cross section of stock returns as well as its role in momentum phenomenon. In other words, both the mean effect and interaction effect are addressed in this paper, like in Zhang (2005) and Jiang, Lee and Zhang (2005).

We find that estimation risk is not significantly priced on U.S. stocks from 1978 to 2009. Sorting portfolio according to the risk proxy does not produce significant return differentials between different groups of stocks. In the multivariate regression analysis, there is also no robust finding that our proxy is significantly related to stock returns.

We find the interaction effect. That is, high estimation risk stocks seem to have stronger momentum. In a five by five sorts, price momentum is only 2.06% for the lowest quintile of estimation risk stocks and more than doubles to 6.29% for the highest quintile of estimation risk stocks. Interaction patterns for earnings momentum and post analyst forecast revision drift are similar. Subsequent analysis finds that there are stronger reversals to price momentum and revision drift portfolios among high estimation risk stocks, suggesting that the momentum theory of continued over-reaction as in Daniel, Hirshleifer and Subrahmanyam (1998) might be correct.

Our study connects to the literature from two directions. Our empirical analysis complements the empirical analysis of KSBD and provides more contents to theoretical debates on estimation risk. Our finding of differential momentum profitability associated with estimation risk sheds some light on the underlying mechanism of momentum.

Our study has limitations. The empirical result is only as strong as the proxy used. Although we fail to confirm the theoretical prediction of KSBD, it is well possible that our proxy is not good at capturing stock estimation risk. Further empirical studies based on alternative proxies are needed to understand the effect of information quality on equilibrium stock returns.

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Appendix A: Variable definition and computation/source

variable	definition	Computation/source
BM	Book-to-market equity ratio	The book equity is as of last fiscal year end, the market equity is as of last month end.
ME	Market equity, a proxy for firm size	As of last month end.
BETA	Market beta	Posting ranking estimates of market beta as in Fama and French (1992).
DEAR	Standard deviation of historical earnings announcement, a proxy for estimation risk	Collect all the earnings announcement return in the last 20 quarters and compute the standard deviation.
EAR	Earnings announcement return	A three-day accumulative abnormal return, where the market return adjusted model is used.
VOLT (%)	Total volatility	Standard deviation of monthly returns from month -13 to month -2.
IVOL (%)	Idiosyncratic volatility	Idiosyncratic volatility estimate as in Ang, Hodrick, Xing and Zhang (2006, 2010) and Fu (2009). Daily stocks are regressed on daily Fama and French three-factor and standard deviation of regression residuals of each month is the idiosyncratic volatility measure of each month.
IO (%)	Institutional ownership	The most recent institutional ownership according to Thompson/13F dataset.
NSKEW	Skewness in stock returns. An increase in NCSKEW means a stock being more “crash prone”.	The negative coefficient of skewness of Chen, Hong and Stein (2001) using the daily stock returns of last quarter.
ANALYST	The number of analysts	Source from IBES.
TURN	Average turnover in the last 36 months	Monthly turnover is defined as total shares trades in this month divided by total shares outstanding.
CVTURN	Coefficient of variation of monthly turnovers of the last 36 months	The same as above.
AMIHU ($\times 10^6$)	Illiquidity measure of Amihud (2002)	Absolute value of daily price change scaled by daily dollar trading volume in last year as in Amihud(2002).
FDISP	Forecast dispersions measure	Standard deviation of earnings estimate divided by the mean estimate, requiring at least three estimates as in Diether, Malloy, and Scherbina (2002).
REV(%)	Average forecast revision in the last three months	Collect monthly revision of mean forecast of earnings (FY1) and then take average of the monthly revisions in the last three months, as in Chan, Jegadeesh and akonishok (1996).
EP	Earnings to price ratio	Defined as earnings per share divided stock price, earnings per share are from the sum of most recent 4 quarters, the price is as of last month end.
DEPS	Deviation of EP ratio, a proxy for fundamental volatility	Standard deviation of quarterly EP ratios in the last 20 quarters. Note the definition of EP ratio is slightly different from the above in

		that this is a figure out of each quarterly disclosure.
ACCR (%)	Total accruals to total assets ratio	The total accruals are defined as $[(\Delta \text{Current Assets} - \Delta \text{Cash}) - (\Delta \text{Current Liabilities} - \Delta \text{Short-term Debt}) - \Delta \text{Taxes Payable}) - \text{Depreciation and Amortization Expenses}] / \text{Total assets}$.
CAPEX (%)	Capital expenditure	Total capital expenditures divided by total assets of the firm. Note that in Compustat the quarterly capital expenditure item is a rolling sum of all previous quarters in the same fiscal year. Adjustments need to be made as in Jegadeesh et al (2004).
SGRT (1+g)	Sales growth ratio	Rolling sum of sales for preceding four quarters divided by the same figure one year ago, defined the same as in Jegadeesh et al (2004)
PIN	Probability of informed trading	This is yearly estimates of probability of informed trading, downloaded From Hvidkjaer's website

Table 1: Summary Statistics

This table presents summary statistics of our sample stocks from Jan 1978 to Dec 2009. Stocks are deleted if their book-to-market ratios are negative or prices below \$5. *BM* is the book-to-market ratio. *ME* is the market value of total shares outstanding expressed in million U.S. dollars. *BETA* is the post ranking estimate of market beta as in Fama and French (1992). *DEAR* is the standard deviation of earnings announcement returns in the last 20 quarters, a proxy for estimation risk. *EAR* is a three-day earnings announcement return. *VOLT* is total stock return volatility, defined as the standard deviation of monthly returns from month -13 to month -2. *IVOL* is idiosyncratic volatility, defined as in Ang, Hodrick, Xing and Zhang (2006). *NSKEW* is the negative skewness measure of Chen, Hong and Stein (2008). *IO* is institutional ownership, available after 1980. *ANALYST* is the number of analysts covering the stock. *TURN* is average turnover and *CVTURN* is the coefficient of variation of turnover in the last 36 months. *AMIHU* is the stock illiquidity measure of Amihud (2002). *FDISP* is analyst forecast dispersion. *REV* is average earnings forecast revision in the last three months. *EP* is the earnings to price ratio. *DEPS* is standard deviation of EP ratios in the last 20 quarters. *ACCR* is the total accrual to total assets ratio. *CAPEX* is total capital expenditure scaled by total assets. *SGRT* is sales growth in gross terms. *PIN* is the probability of informed trading measure of Easley, O'Hara and Hvidkjaer (2002).

	mean	std	P-1	P-25	P-50	P-75	P-99	N
RET (%)	1.17	13.00	-32.30	-5.19	0.63	6.93	39.76	1,153,213
BM	0.77	0.56	0.06	0.38	0.65	1.01	2.77	1,153,213
ME	1,874	7,978	6	60	214	870	31,666	1,153,213
BETA	1.26	0.36	0.55	1.00	1.22	1.51	2.06	1,153,213
DEAR (%)	6.13	3.47	1.67	3.63	5.26	7.71	18.08	1,027,921
EAR (%)	0.43	7.26	-19.26	-2.74	0.13	3.27	22.38	1,058,690
VOLT (%)	11.40	6.84	2.87	6.91	9.83	14.02	35.75	1,153,213
IVOL (%)	9.88	6.36	1.84	5.54	8.30	12.43	32.64	1,145,446
NSKEW	1.68	0.28	1.21	1.54	1.64	1.75	2.75	1,144,834
IO (%)	38.39	28.67	0.00	13.01	35.81	60.47	100.00	1,086,665
ANALYST	5.86	7.46	0	0	3	9	31	1,153,213
TURN	0.09	0.11	0.00	0.03	0.06	0.11	0.54	1,097,262
CVTURN	63.32	30.72	22.08	42.11	56.75	76.29	176.11	1,095,919
AMIHU (X10 ⁶)	1.20	3.96	0.00	0.01	0.07	0.64	19.12	1,087,812
FDISP (X10 ⁶)	0.13	0.43	0.00	0.02	0.04	0.09	2.00	659,054
REV (%)	-0.04	1.78	-4.57	-0.07	0.00	0.07	3.51	666,816
EP	0.04	0.09	-0.32	0.02	0.04	0.07	0.20	1,063,724
DEPS	0.03	0.06	0.00	0.01	0.01	0.03	0.31	1,027,993
ACCR (%)	3.63	12.69	-30.82	-0.74	1.98	6.91	53.60	1,019,085
CAPEX (%)	1.72	2.23	-0.01	0.43	1.06	2.14	11.76	774,447
SGRT(1+g)	1.16	0.38	0.51	1.01	1.10	1.23	2.73	1,047,129
PIN	0.20	0.07	0.07	0.14	0.18	0.23	0.43	339,937

Table 2: Average returns to DEAR portfolios

This table presents one-month ahead average returns to stock portfolios sorted by DEAR from Jan 1978 to Dec 2009 every month. In Panel A and Panel C stock portfolios are equally weighted. In Panel B stock portfolios are market value weighted. *DEAR* is the estimation risk proxy, defined as the standard deviation of all the earnings announcement returns in the last 20 quarters. Panel A and B give results when stocks are one way sorted by *DEAR* into 10 groups. *Raw* is the raw stock return. *CAPM* is the abnormal return from the market model. *Alpha3f* is the abnormal stock return adjusted for the Fama-French (1993) three risk factors. *Alpha4f* is the abnormal return adjusted for the Carhart (1997) four risk factors. *CHAR* is the firm characteristics adjusted stock return of Daniel, Grinblatt, Titman, and Wermers (1997). *NYSE-only* Column reports average raw returns to *DEAR* portfolios formed on NYSE stocks only. In Panel C, stocks are independently sorted by *DEAR* into 5 groups and by another firm characteristic (*ME*, *BM*, or *IVOL*) into 3 groups. The numbers reported in Panel C are average raw stock returns. The *t*-statistics are provided in parentheses.

Panel A: Equally weighted stock portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RAW	CAPM	ALPHA3F	ALPHA4F	CHAR	NYSE only Raw	NYSE only ALPHA3F
1	1.11 (5.97)	0.33 (2.77)	0.12 (1.27)	0.11 (1.14)	-0.10 (-0.84)	1.13 (5.98)	0.13 (1.42)
2	1.18 (5.44)	0.31 (2.63)	0.08 (0.9)	0.08 (0.95)	-0.01 (-0.16)	1.18 (5.42)	0.08 (1.07)
3	1.25 (5.14)	0.32 (2.7)	0.08 (1.01)	0.10 (1.19)	0.02 (0.3)	1.27 (5.09)	0.08 (0.91)
4	1.23 (4.67)	0.27 (2.23)	0.02 (0.27)	0.05 (0.56)	0.01 (0.2)	1.28 (4.78)	0.04 (0.5)
5	1.30 (4.56)	0.29 (2.25)	0.04 (0.5)	0.07 (0.87)	0.07 (1.03)	1.37 (4.88)	0.10 (1.01)
6	1.17 (3.89)	0.14 (1.03)	-0.09 (-1.23)	-0.07 (-1.03)	-0.03 (-0.59)	1.38 (4.64)	0.07 (0.67)
7	1.23 (3.79)	0.15 (1.05)	-0.02 (-0.4)	0.03 (0.47)	0.03 (0.71)	1.44 (4.69)	0.11 (1.02)
8	1.23 (3.51)	0.11 (0.69)	-0.04 (-0.56)	0.02 (0.36)	0.03 (0.44)	1.27 (3.79)	-0.13 (-1.2)
9	1.34 (3.55)	0.17 (0.97)	0.07 (0.87)	0.15 (1.94)	0.16 (2.19)	1.36 (3.89)	-0.05 (-0.47)
10	1.27 (3.03)	0.04 (0.21)	-0.03 (-0.26)	0.11 (1.12)	0.07 (0.71)	1.66 (4.34)	0.21 (1.89)
10th decile - 1st decile	0.16 (0.47)	-0.28 (-1.07)	-0.14 (-0.96)	0.00 (0.03)	0.17 (0.86)	0.52* (1.9)	0.08 (0.59)

Panel B: Value weighted stock portfolios

	RAW	CAPM	ALPHA3F	ALPHA4F
1	1.07 (5.26)	0.20 (1.97)	0.16 (1.83)	0.17 (1.87)
2	0.98 (4.49)	0.08 (0.82)	-0.01 (-0.1)	0.01 (0.14)
3	1.03 (4.14)	0.06 (0.69)	-0.00 (-0.04)	0.01 (0.09)
4	1.14 (4.23)	0.11 (1.34)	0.09 (1)	0.12 (1.3)
5	1.07 (3.83)	0.02 (0.25)	0.01 (0.09)	0.07 (0.82)
6	0.99 (3.38)	-0.08 (-0.7)	-0.14 (-1.25)	-0.06 (-0.53)
7	1.05 (2.95)	-0.14 (-1.05)	-0.09 (-0.66)	0.09 (0.56)
8	1.21 (3.11)	-0.03 (-0.17)	0.09 (0.64)	0.26 (1.95)
9	1.08 (2.58)	-0.21 (-1.11)	-0.06 (-0.39)	0.17 (1.21)
10	1.28 (2.73)	-0.04 (-0.14)	0.14 (0.72)	0.34 (1.85)
10th decile - 1st decile	0.22 (0.57)	-0.24 (-0.77)	-0.02 (-0.07)	0.17 (0.81)

Panel C: Double sorting of DEAR with ME, BM, and IVOL

DEAR * ME						
	L	2	3	4	H	H-L
1	1.13 (5.26)	1.17 (4.48)	1.33 (4.44)	1.39 (4.17)	1.44 (3.72)	0.31 (1.07)
2	1.20 (5.54)	1.31 (4.84)	1.27 (4.19)	1.26 (3.59)	1.20 (2.89)	0.00 (0.01)
3	1.14 (5.43)	1.23 (4.76)	1.14 (3.86)	1.06 (3.04)	1.17 (2.77)	0.03 (0.1)
3-1	0.01 (0.06)	0.06 (0.43)	-0.19 (-1.29)	-0.33* (-1.76)	-0.27 (-1.31)	-0.27 (-1.4)
DEAR * BM						
	L	2	3	4	H	H-L
1	1.10 (4.94)	1.12 (4.3)	0.97 (3.14)	0.97 (2.61)	0.97 (2.25)	-0.13 (-0.42)
2	1.09 (5.21)	1.25 (4.92)	1.30 (4.54)	1.35 (4.01)	1.43 (3.6)	0.34 (1.1)

3	1.20 (5.99)	1.32 (4.91)	1.44 (4.72)	1.42 (4.41)	1.62 (4.4)	0.41 (1.63)
3-1	0.10 (0.81)	0.20 (1.48)	0.47*** (3.14)	0.45** (2.25)	0.65*** (3.35)	0.55*** (3.36)

DEAR * IVOL

	L	2	3	4	H	H-L
1	1.20 (6.3)	1.31 (5.66)	1.31 (5.04)	1.29 (4.69)	1.46 (4.89)	0.26 (1.33)
2	1.18 (5.23)	1.35 (5.01)	1.40 (4.74)	1.50 (4.64)	1.64 (4.44)	0.45* (1.88)
3	0.79 (3.2)	0.87 (2.96)	0.95 (2.86)	0.98 (2.55)	1.14 (2.64)	0.35 (1.08)
3-1	-0.41*** (-3.15)	-0.44*** (-3.42)	-0.36** (-2.38)	-0.31 (-1.57)	-0.32 (-1.4)	0.09 (0.36)

The *t*-statistics greater than 2.58, 1.96, and 1.64 are statistically significant at the 1%, 5%, and 10% level.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Fama-Macbeth regression of monthly stock returns

This table presents Fama-Macbeth regressions of monthly stock returns on the estimation risk proxy and firm characteristics from Jan 1978 to 2009. *COVERAGE* is the logarithm of one plus the number of analysts. The *t*-statistics are provided in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.42*** (4.38)	1.39*** (4.02)	1.89*** (5.09)	1.73*** (3.96)	1.32*** (2.88)	1.49*** (4.37)	2.56*** (5.31)	2.29*** (4.11)
DEAR		1.98 (1.08)	5.19*** (3.41)	3.23 (1.44)	-2.46 (-1.15)	1.09 (0.69)	1.13 (0.69)	2.41** (2.1)
BETA	-0.02 (-0.06)	-0.10 (-0.45)	0.04 (0.18)	-0.09 (-0.38)	-0.26 (-0.92)	-0.05 (-0.25)	-0.19 (-0.86)	-0.12 (-0.62)
ME	-0.02 (-0.55)	-0.02 (-0.53)	-0.07* (-1.84)	-0.07* (-1.7)	0.03 (0.53)	-0.12*** (-3.81)	-0.11*** (-2.85)	-0.17*** (-4.35)
BM	0.22*** (2.96)	0.19*** (2.72)	0.15** (2.28)	0.13* (1.77)	0.16** (2.07)	0.09 (1.47)	0.08 (1.31)	0.07 (1.21)
IVOL			-6.62*** (-8.22)					
NSKEW							-0.65*** (-4.11)	
FDISP				-0.73*** (-5.16)				
PIN					0.46 (0.76)			
AMIHUD						-1.76 (-1.36)	-0.52 (-0.36)	
TURN								-0.12 (-1.37)
CVTURN								-0.34*** (-4.18)
COVERAGE						0.12*** (3.29)	0.18*** (4.76)	0.20*** (4.99)
EP						3.36*** (7.26)	3.33*** (6.36)	3.10*** (6.7)
DEPS						-0.20 (-0.4)	0.17 (0.26)	0.34 (0.5)
ACCR						-0.75*** (-3.76)	-0.73*** (-3.38)	-0.68*** (-3.34)
SGTH						-0.01 (-0.06)	-0.09 (-0.97)	-0.05 (-0.61)
IO							0.00 (0.1)	0.00 (0.25)
CAPEX							-2.67 (-1.44)	-2.35 (-1.27)
LOGPRC								0.10 (1.41)
NOBS	1,153,213	1,027,921	1,023,209	631,886	334,570	964,640	733,479	733,494
GROUP	384	384	384	384	228	384	314	314
R ²	3.8%	4.4%	4.8%	5.9%	4.2%	6.5%	6.6%	7.0%

The *t*-statistics greater than 2.58, 1.96, and 1.64 are statistically significant at the 1%, 5%, and 10% level.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Differential momentum and drift effect -- sort evidence

This table presents a six-month holding period return to stock portfolios sorted sequentially by *DEAR* and the momentum or drift variable. Panel A reports price momentum with the momentum variable being a cumulative stock return from month -7 to month -2, *PRET*. Panel B reports earnings momentum with the momentum variable being a recent earnings announcement return, *EAR*. Panel C reports analyst forecast revision drift with the drift variable being the average analyst forecast revision in the past three months, *REV*. The *t*-statistics are provided in parentheses.

Panel A: price momentum

	L	2	3	4	H	H_L
PRET						
1	5.88 (8.8)	5.76 (7.26)	5.24 (6.25)	4.85 (5.26)	5.36 (5.18)	-0.52 (-0.74)
2	7.15 (13)	7.20 (10.96)	7.31 (10.32)	7.27 (8.93)	7.91 (8.51)	0.76 (1.12)
3	7.21 (13.87)	7.96 (13.22)	8.10 (12.04)	8.62 (11.2)	8.84 (9.62)	1.63** (2.3)
4	7.41 (14.49)	8.49 (14.27)	8.44 (12.71)	9.04 (11.19)	10.06 (10.4)	2.65*** (3.41)
5	7.94 (14.22)	9.76 (14.15)	10.09 (13.1)	11.18 (11.56)	11.66 (9.77)	3.71*** (3.92)
5-1	2.06*** (4.72)	4.00*** (7.71)	4.85*** (8.93)	6.33*** (9.78)	6.29*** (8.85)	4.23*** (6.83)

Panel B: earnings momentum

	L	2	3	4	H	H_L
EAR						
1	6.61 (11.56)	6.88 (10.35)	6.04 (8.12)	6.10 (6.99)	6.37 (6.21)	-0.24 (-0.31)
2	6.97 (13.21)	7.58 (11.54)	7.87 (11.07)	7.84 (9.45)	8.24 (8.66)	1.27* (1.75)
3	7.17 (13.64)	7.87 (12.56)	7.67 (11.45)	8.23 (10.38)	9.03 (9.95)	1.86*** (2.77)
4	7.43 (13.84)	8.33 (12.99)	8.45 (12.19)	9.03 (11.08)	9.21 (9.61)	1.79** (2.52)
5	7.50 (13.61)	8.61 (13.16)	9.23 (12.39)	9.94 (11.47)	11.26 (10.22)	3.76*** (4.46)
5-1	0.89*** (5)	1.73*** (8.48)	3.20*** (13.06)	3.84*** (13.03)	4.89*** (13.08)	4.00*** (10.27)

Panel C: revision drift

	L	2	3	4	H	H_L
REV						
1	5.22 (7.79)	4.64 (5.86)	3.99 (4.67)	3.56 (3.7)	3.11 (3.07)	-2.11*** (-2.94)
2	6.57 (11.62)	7.11 (11.17)	6.47 (9.03)	6.19 (7.44)	6.34 (6.24)	-0.21 (-0.27)
3	7.60 (13.99)	8.57 (13.98)	8.76 (13.26)	8.80 (11.2)	9.59 (9.49)	2.00** (2.47)
4	7.87 (14.58)	8.89 (13.63)	9.37 (12.87)	9.38 (10.73)	10.31 (9.67)	2.44*** (2.87)
5	7.84 (13.83)	8.73 (12.84)	8.27 (10.86)	9.08 (9.74)	9.10 (8.65)	1.27 (1.6)
5-1	2.62*** (7.92)	4.09*** (10.58)	4.27*** (9.74)	5.52*** (12.01)	6.00*** (11.74)	3.38*** (6.5)

The *t*-statistics greater than 2.58, 1.96, and 1.64 are statistically significant at the 1%, 5%, and 10% level.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Differential momentum and drift effect -- regression evidence

This table shows estimation risk causing differential momentum and drift effects using the Fama-Macbeth regression approach from 1978 to 2009. In regressions the decile ranks of *DEAR*, *PRET*, *EAR* and *REV* are used instead of original values. In each month stocks are firstly sorted into deciles by *DEAR* and then within each *DEAR* decile further sorted into deciles by the momentum or drift variable (*PRET*, *EAR* or *REV*). *PRET* is a cumulative return from month -7 to month -2. *EAR* is a three-day earnings announcement return. *REV* is the average analyst forecast revision in the past three months. The *t*-statistics are provided in parentheses.

Panel A: price momentum (383 months)

	Intercept	DEAR	PRET	DEAR*PRET	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGTH	NOBS
(1)	7.26*** (7.55)	0.17*** (2.95)	0.48*** (8.3)		-0.08 (-0.14)	-0.32*** (-3.89)	1.11*** (4.97)								1,006,122
(2)	8.20*** (8.95)	-0.05 (-0.96)	0.26*** (5.09)	0.05*** (5.93)	-0.11 (-0.21)	-0.30*** (-3.69)	1.09*** (4.9)								1,006,122
(3)	10.59*** (10.74)	0.11** (2.24)	0.10* (1.76)	0.03*** (3.53)	0.15 (0.29)	-0.44*** (-5.03)	0.97*** (4.7)	-27.48*** (-12.39)	2.37*** (6.48)	-0.70 (-0.2)		-3.74*** (-2.82)			992,689
(4)	10.73*** (11.48)	0.13*** (2.7)	0.09* (1.66)	0.03*** (3.49)	0.48 (1)	-0.45*** (-5.31)	0.71*** (3.74)	-27.23*** (-13.25)	2.47*** (6.62)	1.49 (0.41)	1.49 (0.97)	-2.70* (-1.66)	-4.63*** (-9.41)	-0.47* (-1.83)	948,818

Panel B: earnings momentum (383 months)

	Intercept	DEAR	PRET	DEAR*EAR	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGTH	NOBS	R ²
(1)	7.54*** (7.8)	0.18*** (3.17)	0.31*** (16.59)			0.03 (0.05)	-0.26*** (-3.04)	1.25*** (5.78)							984,552	5.12%
(2)	8.54*** (8.83)	-0.04 (-0.74)	0.09*** (4.63)	0.05*** (10.39)		0.03 (0.05)	-0.26*** (-3.02)	1.23*** (5.71)							984,552	5.19%
(3)	10.47*** (9.82)	0.10** (1.98)	-0.03 (-1.07)	0.03*** (6.2)	1.74*** (6.2)	0.39 (0.76)	-0.36*** (-3.97)	1.05*** (5.18)	-27.46*** (-11.83)	7.76** (2.09)		-2.53* (-1.9)			971,370	6.09%
(4)	10.34*** (10.01)	0.10** (2.11)	-0.04 (-1.43)	0.03*** (6.49)	1.70*** (6)	0.74 (1.49)	-0.38*** (-4.21)	0.83*** (4.55)	-26.55*** (-11.9)	7.99** (2.19)	1.14 (0.67)	-1.24 (-0.79)	-3.89*** (-7.68)	-0.24 (-0.85)	946,908	6.95%

Panel C: revision drift (383 months)

	Intercept	DEAR	PRET	DEAR*REV	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGTH	NOBS	R ²
(1)	7.28*** (6.24)	0.12* (1.92)	0.54*** (13.67)		-0.17 (-0.3)	-0.34*** (-3.28)	0.99*** (4.29)								631,067	6.9%
(2)	8.25*** (7.03)	-0.14** (-2.15)	0.32*** (8.11)	0.06*** (7.75)	-0.17 (-0.3)	-0.34*** (-3.28)	0.98*** (4.26)								631,067	7.1%
(3)	9.83*** (8.05)	-0.03 (-0.53)	0.24*** (5.6)	0.05*** (6.28)	0.14 (0.28)	-0.43*** (-4.14)	0.86*** (4.04)	-23.95*** (-8.33)	1.59*** (3.99)	-7.88 (-0.26)		-3.06* (-1.68)			625,706	8.3%
(4)	10.35*** (8.38)	-0.02 (-0.35)	0.25*** (5.88)	0.05*** (6.36)	0.44 (0.89)	-0.44*** (-4.29)	0.45** (2.34)	-22.67*** (-7.96)	1.66*** (4.2)	13.52 (0.43)	1.89 (0.92)	-1.01 (-0.47)	-4.85*** (-7.92)	-1.04*** (-2.92)	606,406	9.6%

The *t*-statistics greater than 2.58, 1.96, and 1.64 are statistically significant at the 1%, 5%, and 10% level.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Reversal indication

This table presents average return to the momentum or drift hedge portfolio in every six-month period in the 5 years after portfolio formation. This table is continuation of Table 4. Within the top and bottom quintile of *DEAR* stocks, hedge portfolios are formed based on the momentum or drift variable. Panel A, B and C reports hedge portfolios of price momentum, earnings momentum and revision drift, respectively. The *t*-statistics are provided in parentheses.

Panel A: price momentum portfolios

		1-6	7-12	13-18	19-24	25-30	31-36	37-42	43-48	49-54	55-60
DEAR	PRET										
1	1	5.88 (8.8)	5.92 (10.35)	6.63 (10.85)	6.01 (9.97)	6.43 (10.79)	6.77 (10.37)	7.15 (10.75)	6.87 (9.97)	7.76 (11.75)	7.21 (10.67)
	5	7.94 (14.22)	7.14 (13.19)	6.54 (11.2)	6.75 (11.42)	6.50 (10.46)	6.45 (11.02)	6.17 (10.15)	6.91 (11.37)	6.92 (10.59)	7.08 (10.66)
	diff	2.06*** (4.72)	1.23*** (6.82)	-0.09 (-0.45)	0.74*** (3.68)	0.07 (0.31)	-0.32 (-1.46)	-0.98*** (-4.35)	0.04 (0.17)	-0.84*** (-3.41)	-0.13 (-0.53)
5	1	5.36 (5.18)	7.37 (7.71)	8.25 (7.78)	9.62 (7.91)	10.55 (8.57)	8.93 (7.72)	8.90 (7.63)	8.62 (7.48)	9.86 (8.57)	8.96 (7.86)
	5	11.66 (9.77)	6.10 (5.7)	5.96 (6.41)	7.70 (7.61)	7.00 (6.68)	8.17 (7.38)	8.95 (7.31)	10.28 (8.6)	9.09 (7.43)	8.96 (7.71)
	diff	6.29*** (8.85)	-1.27*** (-3.08)	-2.29*** (-6.48)	-1.91*** (-4.66)	-3.55*** (-8.73)	-0.76* (-1.73)	0.05 (0.11)	1.66*** (3.68)	-0.77* (-1.65)	0.00 (0.01)

Panel B: earnings momentum portfolios

		1-6	7-12	13-18	19-24	25-30	31-36	37-42	43-48	49-54	55-60
DEAR	CAR										
	1										
1	1	6.61 (11.56)	6.66 (12.71)	6.25 (11.26))	6.25 (11.19))	6.98 (11.88)	6.43 (10.98)	6.57 (11)	6.41 (10.77))	7.32 (12.02)	7.09 (11.51))
	5	7.5 (13.61)	7.25 (13.82)	6.56 (12.12))	6.55 (11.87))	6.38 (11.18)	6.50 (11.83)	6.13 (10.5)	6.85 (11.3)	6.74 (11.37)	7.11 (10.79))
	diff	0.89** (5)	0.59** (3.47)	0.31* (1.78)	0.29 (1.59)	0.61*** (-3.02)	0.06 (0.33)	0.45** (-2.16)	0.44** (2.08)	0.57** (-2.56)	0.02 (0.1)
5	1	6.37 (6.21)	6.67 (7.17)	7.88 (7.96)	7.97 (7.29)	9.59 (8.05)	8.09 (7.31)	8.78 (7.6)	8.86 (7.84)	9.35 (8.05)	8.51 (7.52)
	5	11.26	8.32	8.06	8.62	8.89	9.14	9.67	9.57	9.16	9.06

	(10.22)	(8.17)	(8.05)	(9.06)	(8.19)	(8.85)	(8.19)	(8.58)	(8.2)	(8.04)
	4.89**	1.65**				1.05**				
diff	*	*	0.17	0.65*	-0.71*	*	0.89**	0.71*	-0.18	0.54
	(13.08)	(4.05)	(0.49)	(1.78)	(-1.73)	(2.67)	(2.1)	(1.65)	(-0.41)	(1.19)

Panel C: revision drift portfolios

		1-6	7-12	13-18	19-24	25-30	31-36	37-42	43-48	49-54	55-60
DEAR	REV										
	1	5.22	6.54	5.96	6.33	6.08	6.45	6.56	6.85	6.71	7.15
		(7.79)	(10.6)	(8.96)	(9.11)	(8.89)	(8.69)	(8.71)	(8.17)	(9.16)	(9.1)
1	5	7.84	6.51	6.41	6.49	6.29	6.60	6.15	6.73	6.42	7.01
		(13.83)	(11.44)	(10.94)	(10.61)	(10.04)	(10.23)	(9.04)	(9.93)	(9.34)	(9.44)
	diff	2.62***	-0.03	0.45**	0.16	0.21	0.15	-0.41	-0.12	-0.28	-0.14
		(7.92)	(-0.13)	(2.03)	(0.67)	(0.84)	(0.57)	(-1.49)	(-0.38)	(-1.01)	(-0.47)
	1	3.11	5.87	7.11	7.88	8.97	8.05	7.47	7.40	8.87	8.17
		(3.07)	(4.95)	(5.87)	(5.75)	(5.98)	(5.58)	(6.07)	(5.86)	(6.19)	(6.16)
5	5	9.1	4.90	6.66	6.86	7.43	7.67	7.93	7.83	8.21	7.37
		(8.65)	(5.52)	(6.05)	(6.5)	(6.54)	(6.68)	(6.53)	(7)	(6.63)	(6.51)
	diff	6.00***	-0.97*	-0.45	-1.01*	-1.54***	-0.39	0.46	0.43	-0.66	-0.80
		(11.74)	(-1.73)	(-0.9)	(-1.85)	(-2.62)	(-0.66)	(0.75)	(0.67)	(-0.93)	(-1.18)

The t-statistics greater than 2.58, 1.96, and 1.64 are statistically significant at the 1%, 5%, and 10% level.

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Robustness tests

This table conducts robustness tests. Panel A divides the sample period into two sub-periods, 1978-1993 and 1995-2009. Panel B uses two alternative ways of computing the proxy for estimation risk. The first way is the average absolute value of earnings announcement returns in the last 20 quarters, denoted as “abs.”. The second way is the standard deviation of earnings announcement returns in the last 16 quarters, denoted as “16 qtr”. Within each panel, there are four sub-panels showing the pricing of estimation risk and the differential momentum effect associated with estimation risk. The *t*-statistics are provided in parentheses.

Panel A: sub-period analysis

A.1 Monthly stock return

	Intercept	DEAR	BETA	ME	BM	AMIHU	ANALYST	EP	DEPS	ACCR	SGRT	NOBS	R ²
1978-1993	1.53*** (3.84)	1.15 (0.53)	-0.06 (-0.24)	-0.11*** (-2.87)	0.15* (1.91)	1.07 (0.72)	0.07 (1.38)	3.91*** (6.81)	0.32 (0.51)	-0.81*** (-2.7)	0.28* (1.68)	378,489	5.6%
1993-2009	1.32** (2.19)	3.12 (1.2)	-0.03 (-0.1)	-0.09 (-1.63)	0.07 (0.82)	-1.92 (-0.93)	0.16*** (2.91)	2.55*** (2.98)	0.02 (0.03)	-0.38 (-1.26)	-0.19 (-1.63)	586,152	5.9%

A2. Price momentum

	Intercept	DEAR	PRET	DEAR*PRET	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGRT	NOBS
1978-1993	11.82*** (11.03)	-0.01 (-0.16)	0.13 (1.65)	0.04*** (5)	0.42 (0.63)	-0.59*** (-5.66)	0.80*** (3.3)	-34.78*** (-12.46)	2.71*** (4.67)	14.43*** (3.37)	13.71*** (8.21)	-1.42 (-0.83)	-7.27*** (-11.1)	0.26 (0.61)	373,489
1993-2009	8.74*** (5.75)	0.26*** (3.21)	0.07 (0.9)	0.02 (1.27)	0.63 (0.9)	-0.34** (-2.5)	0.36 (1.21)	-16.02*** (-5.64)	2.10*** (4.34)	-14.25** (-2.43)	4.22 (1.58)	-0.69 (-0.24)	-3.18*** (-4.52)	-1.62*** (-6.15)	575,489

A3. Earnings momentum

	Intercept	DEAR	EAR	DEAR*EAR	BETA	ME	BM	IVOL	DEAR * IVOL	AMIHU	EP	DEPS	ACCR	SGRT	NOBS
1978-1993	11.98*** (10.12)	-0.05 (-1.02)	0.02 (0.51)	0.05*** (7.89)	0.38 (0.58)	-0.57*** (-5.49)	0.93*** (3.97)	-33.40*** (-12)	1.37*** (3.15)	21.04*** (4.4)	13.26*** (7.46)	-0.51 (-0.3)	-6.42*** (-9.55)	0.68 (1.44)	373,489
1993-2009	7.88*** (4.69)	0.25*** (2.99)	-0.09*** (-2.73)	0.02** (2.03)	1.18 (1.62)	-0.20 (-1.41)	0.47* (1.69)	-16.67*** (-4.92)	2.05*** (5.56)	-7.71 (-1.4)	3.92 (1.32)	1.44 (0.53)	-2.51*** (-3.44)	-1.56*** (-5.86)	575,489

A4. Revision drift

	Intercept	DEAR	REV	DEAR*REV	BETA	ME	BM	IVOL	DEAR * IVOL	AMIHU	EP	STDEPS	ACCR	SGRT	NOBS
1978-1993	13.31*** (8.84)	-0.18*** (-3.29)	0.19*** (3.18)	0.07*** (7.53)	0.26 (0.36)	-0.71*** (-5.75)	0.85*** (3.39)	-39.54*** (-10.83)	3.08*** (5.02)	74.02** (2.25)	3.69 (1.43)	2.02 (0.75)	-7.60*** (-8.96)	0.40 (0.63)	231
1993-2009	7.45*** (3.85)	0.14 (1.51)	0.30*** (5.09)	0.03** (2.23)	0.61 (0.88)	-0.17 (-1.07)	0.05 (0.17)	-5.63 (-1.4)	0.24 (0.5)	-47.83 (-0.9)	0.03 (0.01)	-4.04 (-1.2)	-2.10** (-2.49)	-2.47*** (-7.98)	374

Panel B: alternative ways of computing the estimation risk proxy

B.1 Monthly stock return

	Intercept	DEAR	BETA	ME	BM	AMIHU	COVERAGE	EP	DEPS	ACCR	SGRT	NOBS	R ²
abs.	1.43*** (4)	2.89 (1.35)	-0.05 (-0.22)	-0.10*** (-3.05)	0.11* (1.9)	-0.49 (-0.39)	0.12*** (3.12)	3.23*** (6.27)	0.18 (0.35)	-0.60*** (-2.81)	0.04 (0.41)	964,714	5.73%
16 qtr	1.44*** (4.06)	1.34 (1.01)	-0.02 (-0.1)	-0.11*** (-3.15)	0.11* (1.78)	-0.46 (-0.36)	0.12*** (3.17)	3.24*** (6.23)	0.27 (0.53)	-0.59*** (-2.72)	0.05 (0.5)	963,898	5.67%

B.2 Price momentum

	Intercept	DEAR	PRET	DEAR*PRET	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGRT	NOBS
abs.	10.34*** (11.11)	0.14*** (2.63)	0.09 (1.55)	0.03*** (4.24)	0.41 (0.87)	-0.45*** (-5.31)	0.60*** (3.2)	-25.19*** (-12.58)	2.25*** (6.09)	0.51 (0.14)	8.92*** (5.58)	-1.13 (-0.69)	-5.26*** (-10.76)	-0.71*** (-2.82)	948,842
16 qtr	10.26*** (11.04)	0.14*** (3.11)	0.11* (1.88)	0.03*** (3.26)	0.51 (1.06)	-0.47*** (-5.52)	0.57*** (3)	-26.00*** (-12.52)	2.47*** (6.58)	-0.33 (-0.09)	9.02*** (5.66)	-0.88 (-0.55)	-5.22*** (-10.63)	-0.66*** (-2.63)	947,971

B.3 Earnings momentum

	Intercept	DEAR	EAR	DEAR*EAR	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGRT	NOBS
abs.	9.98*** (9.72)	0.12** (2.27)	-0.04* (-1.73)	0.04*** (7.66)	0.64 (1.32)	-0.37*** (-4.19)	0.73*** (4.06)	-24.67*** (-11.15)	1.52*** (5.25)	7.09* (1.92)	8.57*** (4.91)	0.35 (0.22)	-4.52*** (-8.99)	-0.48* (-1.73)	946,932
16 qtr	9.92***	0.11**	-0.04	0.03***	0.78	-0.39***	0.70***	-25.54***	1.76***	6.14*	8.67***	0.63	-4.45***	-0.42	946,072

(9.61)	(2.34)	(-1.63)	(6.46)	(1.56)	(-4.4)	(3.81)	(-11.4)	(6.19)	(1.66)	(4.98)	(0.4)	(-8.8)	(-1.54)
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B.4 Revision drift

	Intercept	DEAR	REV	DEAR* REV	BETA	ME	BM	IVOL	DEAR*IVOL	AMIHU	EP	DEPS	ACCR	SGRT	NOBS
abs.	10.35*** (8.37)	-0.00 (-0.06)	0.24*** (5.63)	0.05*** (6.72)	0.32 (0.65)	-0.42*** (-4.12)	0.47** (2.5)	-22.57*** (-8)	1.56*** (3.84)	16.67 (0.55)	1.87 (0.91)	-1.07 (-0.5)	-4.91*** (-8.05)	-1.06*** (-2.98)	606,414
16 qtr	10.43*** (8.48)	0.01 (0.18)	0.23*** (5.42)	0.04*** (6.23)	0.38 (0.75)	-0.44*** (-4.28)	0.45** (2.33)	-24.22*** (-8.45)	1.97*** (5)	12.62 (0.4)	1.83 (0.88)	-0.83 (-0.39)	-4.83*** (-7.89)	-1.04*** (-2.92)	606,175

The t-statistics greater than 2.58, 1.96, and 1.64 are statistically significant at the 1%, 5%, and 10% level.

*** p<0.01, ** p<0.05, * p<0.1

Essay Three: Informed Trading and Mutual Fund Alpha

Abstract*

Motivated by the literature's extensive use of the earnings announcement effects to show the informed trading of financial institutions, we use a measure of mutual funds' investment skills or information superiority based on their buy trades. If a mutual fund buys stocks that subsequently enjoy high earnings announcement returns, the fund is either skilled or informed by this measure. The measure successfully predicts fund winners from 1984 to 2009. The top performing decile of mutual funds beats the bottom decile by 47 basis points a quarter. The measure shows persistence over time. We infer that the inherent investment talent or information advantage of fund managers contributes to alpha.

Keywords: earnings announcement, mutual fund alpha, informed trading

JEL: G11 G12 G14

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I. Introduction

The cross-section of fund alphas has always been an interesting topic. Fama and French (2010) show that the aggregate value-weighted portfolio of active mutual funds is close to the market portfolio. They posit that the negative alphas of some funds have to be balanced by the positive alphas of other funds. But is the variation of fund alphas simply a matter of chance? To refute this idea, they use the bootstrap simulation technique and find evidence of managerial skills.⁴³ Other researchers have used the tests of persistence in fund performance (Carhart (1997), Grinblatt and Titman (1992)), stock holding characteristics (Cremers and Petajisto (2009), Kacperczyk, Sialm and Zheng (2005)), and unrecorded fund actions (Kacperczyk, Sialm and Zheng (2008)), among other interesting tests, to examine the existence of fund skills.

We also seek to explain why there is variation in the alpha of different funds. We hypothesize that informed trading and mutual fund alpha are two sides of the same coin. Funds that appear to be informed traders in the past are expected to deliver greater alphas in the future. We assume that informed trading is made possible by the investment skills or information superiority of fund managers, and we predict that mutual fund shows persistence in informed trading.

To test our hypothesis, we quantify the amount of informed trading of mutual funds in each quarter, and use this information about informed trading to predict future fund return. This measure is motivated by many studies on earnings announcement effects. In these studies, the pre-event trading of certain financial institutions is shown to be informed because stocks they purchase subsequently realize greater earnings announcement returns (EAR). In line with these studies, if a mutual fund increases its holdings in stocks before they report higher than expected

⁴³The bootstrap simulations in Kosowski, Timmermann, Wermers and White (2006) produce stronger evidence for fund skills, as noted by Fama and French (2010).

earnings, its trading is considered informed, and the greater the increase in holding and the larger the announcement return, the more informed is the trading.

This measure is based on fund trades, and is constructed by multiplying the change in stock holding by the magnitude of EAR. In other words, the trading amount is interacted with the trading outcome. The EAR is defined as the 3-day accumulated excess stock return around the announcement date. If a fund holds multiple stocks, the results from multiplying the weight change and EAR of individual stocks owned by the fund are summed to produce the measure for the fund. According to this measure, if a fund increases its holding in many stocks with large positive EAR, the fund is relatively more skilled or informed.⁴⁴

In defining this measure, we divide trades into buy and sell trades. This division is motivated by prior studies that show different information roles for the two types of trades. For example, Chen, Jagadeesh, and Wermers (2000) show that stocks purchased by funds significantly outperform stocks they sell. Alexander, Cici, and Gibson (2007) show that fund managers make valuation motivated buys while the pattern is weaker for sells. These findings are not surprising because mutual funds are typically long-only investors. Buy trades likely reflect the fact that fund managers believe stocks are undervalued. On the other hand, sell trades can be the result of a liquidity need. Mutual funds may find it necessary to liquidate certain positions and buy better stocks. Also, mutual funds may have to sell stocks when faced with large fund outflows.

As a result of the findings discussed above, we expect the measure based on buy trades to be more informative and useful than the measure based on sell trades, and we expect it to be positively associated with fund returns. The prediction is not as clear, however, for the measure based on sell trades. The sell trades-based measure can be positively related to fund return if sell trades are

⁴⁴ We are aware of Wermers, Yao and Zhao (2010) who also develop and use a measure similar to our in nature. Our first version was dated earlier than Wermers, Yao and Zhao (2010). The earlier versions of their paper do not have such a measure. We show that their measure is related to ours in a meaningful way, but it is not significantly related to fund return. More discussions can be found in Section IV.

information driven. It can also be negatively related to fund return when sell trades are used to replace stocks and both old and new stocks are undervalued. The sell trades-based measure is not obviously related to future fund return when sell trades are used to deal with investor outflows.

We find that the buy trades-based measure successfully predicts fund winners from 1984 to 2009. The fund return differential between the top and bottom decile funds sorted by this measure is 47 basis points a quarter before adjusting for risk and 37 basis points after adjusting for Carhart's (1997) four risk factors. The positive relationship between this measure and fund returns holds when fund characteristics and the post-earnings announcement drift are controlled in the regression. Return predictability of the measure comes from the ability of mutual funds to select stocks, which is revealed by our analysis using the characteristics-based fund performance measure developed by Daniel, Grinblatt, Titman, and Wermers (1997).

The fund return predictability of this measure is economically large and comparable to existing fund studies. For instance, Kacperczyk et al. (2005) find a 32 basis points a quarter return differential between the top and bottom decile funds sorted by their industry concentration measure for their sample funds from 1984 to 2003 after adjusting for Carhart's four risk factors. The results of our study show that the differential is 37 basis points a quarter. Cremers and Petajisto (2009) use the measure of deviation from benchmark portfolios and find the return differential between the top and bottom quintile funds is 64 basis points a quarter after adjusting for the benchmark index return specific to each fund.⁴⁵ In our study, we find the return differential between the top and bottom quintile funds is 29 basis points a quarter after adjusting for Carhart's four risk factors. Kacperczyk et al. (2008) use the return gap measure and find the return differential between the first- and second-half funds is 9 basis points a month before adjusting for

⁴⁵Sensoy (2009) finds that approximately one-third of U.S. equity funds specify a benchmark in the fund prospectus that does not match the fund's actual style. His study suggests that this strategic fund behavior improves fund flows.

risk and 7 basis points after adjusting for Carhart's four risk factors from 1984 to 2003. In our study, we find 23 basis points a quarter and 18 basis points a quarter, respectively.

Apart from finding fund return predictability, we also find persistence for this measure, which supports the existence of fund managers' investment skills or information advantages. Funds with large values of the measure in one quarter tend to have large values as well in the prior and subsequent eight quarters. The measure of prior quarters can help predict future fund returns. Such return predictability is robust when lagged fund alpha is included in the regressions.

Our work contributes to the knowledge about how active management translates into mutual funds alphas. The cross-sectional variation in fund alphas can be explained by their differing ability to carry out informed trading. This informed trading, which can be seen in their informed trades before corporate earnings announcements, appears to be the result of the investment skills or information superiority of the management of some mutual funds. Such skills or information superiority shows persistence.

We use the earnings announcement events to show mutual funds' informed trading. Therefore, our work complements the following studies that show mutual funds carry out informed trading in many other aspects. Wermers (2000) examines the stock-selection skills of mutual funds from 1975 to 1994 and finds that although the annual net returns of mutual funds underperformed the market by 1% the stocks picked by the funds outperform the market by 1.3%. Coval and Moskowitz (2001) show that mutual funds trade local stocks at an information advantage and earns substantial abnormal returns. Alexander et al. (2007) find that mutual funds are conscious about the stocks they want to buy and keep. When faced with large investor outflows, mutual funds opt to retain certain stocks in the portfolio. The decision is motivated by the belief that these stocks are heavily undervalued, and these stocks are later found to beat the market. Jiang, Yao and Yu (2007) investigate the market timing skills of mutual funds by examining their holdings. Ali,

Chen, Yao and Yu (2008) investigate whether mutual funds are capable of profiting from financial anomalies, and they find that some mutual funds profit from the accrual anomaly by deliberately seeking exposure to low accrual stocks that deliver high future returns.

In addition, mutual funds even draw on personal connections between fund managers and corporate board members to choose good stocks. Cohen, Frazzini and Malloy (2008) find that mutual funds often base their level of investment on personal connections, and this type of investment has a higher return than investment that is not based on personal connections. More generally, Kacperczyk et al. (2005) show that fund managers create value by concentrating their portfolios in industries in which they may have information advantages. Their fund-level industry concentration measure predicts fund alpha. Similarly, Cremers and Petajisto (2009) find that mutual funds purposely deviate their holdings from the index or benchmark portfolios. They show that funds with larger deviations realize higher future returns. Da, Gao, and Jagannathan (2010) divide mutual funds' stock- selection skills into impatient trading and liquidity provision. They find that the highest returns are the result of impatient trading.

Our work is connected to those studies that motivate us to measure the informed trading of mutual funds. Baik, Kang and Kim (2010) show that local institutional investors have more information about local stocks than non-local investors. Stocks in which local institutional investors have increased their weight earn more than the matching stocks at the next earnings announcement by 0.96%. Ke and Petroni (2004) find that transient institutional investors possess information that allows them to avoid negative stock price shocks associated with the end of a string of consecutive earnings increases. Baker, Litov, Wachter and Wurgler (2010) investigate the stock-selection skill of mutual fund managers by examining the EAR of the stocks they hold and trade. At the stock level they find that the average fund's recent buys significantly outperform its recent sells around subsequent earnings announcements. More studies that examine informed trading from the

perspective of EAR can also be found in Bushee, and Goodman (2007), Chrisophe, Ferri, and Angel (2004), and Kim and Verrecchia (1997).

Our work, however, differs from the above studies. Those studies illustrate the existence of informed trading, and they suggest that a certain group of investors is more informed than other investors. They do not analyze how performance differs among this group of informed investors, but we do. For example, Baker et al. (2010) find stock-level evidence that shows mutual funds as a group make informed trading. They show that stocks held or purchased by mutual funds subsequently have positive EAR. They do not answer why fund alphas should vary, and if there is any regularity among such variations.

In contrast, the emphasis of our study is on the individual fund. Even though mutual funds as a group has been shown to make informed trading, much can still be learned from further examining the cross-sectional variation among funds. We explain how funds differ from one another in terms of informed trading and how these differences lead to different fund alphas. Our study has implications for fund investors because the measure seems to capture the skills or information advantages of fund managers.

The remainder of this paper is organized as follows. In section II, we form and describe our sample. In section III, we define the measure of the investment skills or information superiority for mutual funds. We also explain the fund performance measures and major control variables in this section. Section IV contains the empirical tests and shows the fund-return predictability of the measure. Section V concludes the paper.

II. Sample formation

We use the sample formation procedures of Kacperczyk et al. (2005) and develop a sample of mutual funds from 1984 to 2009 that is formed by matching the Thomson/CDA stock holding

database with the CRSP mutual fund database. We merge the Thomson/CDA and CRSP mutual fund databases using MFLINKS' Tables 1 and 2 provided by Wharton Research Data Services (WRDS).

Thomson/CDA contains mutual funds' quarterly stock holdings.⁴⁶ The primary source for these data is SEC N-30D filings, which are only semi-annual.⁴⁷ Note, however, that many mutual funds voluntarily report holdings quarterly and Thomson/CDA uses fund prospectuses and contacts mutual fund management companies to increase the reporting frequency of mutual funds in its database. As a result, quarterly reports are obtained for more than 80% of all funds (see Wermers (2000)). In our study, 94% of our sample report on a quarterly basis.

The CRSP mutual fund database is free of survivorship bias. It provides information about monthly fund returns, total net assets (TNA), fee structures, investment objectives, and other fund characteristics.⁴⁸ The database is updated quarterly and distributed with a quarterly lag. The CRSP mutual fund database lists each fund's share class as a separate fund. We combine all the fund classes into one single fund. Following Yan (2008), we sum TNA for each share class to obtain TNA for the fund. For all other fund characteristics, we use a TNA-weighted average across all share classes.

We replace the prices of each fund's reported stock holdings in the holding database with the prices in CRSP stock files to ensure accuracy. To construct the measure of the investment skills or information superiority of mutual funds, we obtain the earnings report date and earnings number for all stocks from the Compustat database. To analyze the effect of mutual funds' investment styles on the return predictability of the measure, we obtain the book-to-market ratio of all the

⁴⁶After 1986, it is relatively free of survivorship bias (Fama and French (2010)).

⁴⁷The requirement was quarterly before 1985, semi-annual after that until 2003 and was quarterly again after 2004.

⁴⁸The monthly TNA is available starting from 1991.

stocks from the website of Russ Wermers.⁴⁹ Also, we obtain the characteristics-based benchmark return and the stock assignments data from this website to construct Daniel et al.'s (1997) fund return measure.

In addition, we only include mutual funds in our sample that are diversified domestic equity mutual funds after matching the Thomson/CDA stock holding database to the CRSP mutual fund database. We use investment codes from the CRSP mutual fund database to identify these funds.⁵⁰ As a result of this procedure, we delete sector, balanced, and international funds. We also drop index funds with names that contain the word Index. We further require funds to have at least one million TNA and hold at least 20 stocks. Finally, we require funds to have at least 24-months return history to estimate abnormal fund returns.

Table 1 is about here.

Table 1 summarizes our sample. Our sample consists of 2,822 distinct domestic equity mutual funds from 1984 to 2009,⁵¹ and there are 82,014 fund-quarter observations. The number of observations for *CAR1_BUY* and *CAR1_SELL* is slightly smaller because there are no buys or sells for some fund quarters. The average quarterly return of these funds from 1984 to 2009 is 1.94%, with a standard deviation of 10.32%. This high standard deviation indicates there are either large time-series or cross-sectional variations in fund returns. The median fund size by TNA is 161 million USD while the mean is 1,283 million USD. There are a few truly large mutual funds in the industry, and this situation right skews the variable TNA (see, for example, Chen, Hong, Huang, and Kubik (2004)). Therefore, we use log TNA in the multivariate regression, which is discussed in later sections of this paper. The fund-expense ratio has a mean of 1.33% and a median of 1.30%.

⁴⁹The DGTW benchmarks are found on the following website:

<http://www.smith.umd.edu/faculty/rwermers/ftp/Dgtw/coverpage.htm>

⁵⁰Funds are selected based on Strategic Insights, Lipper, Wiesenberger, and Policy objective codes. Funds with Strategic Insights objective codes AGG, ING, MID, GMC, GRI, GRO, and SCG, Lipper objective codes EI, EIEI, ELCC, G, GI, LCCE, LCGE, LCVE, MC, and MCCE, Wiesenberger objective codes G, G-I, IEQ, GCI, LTG, MCG, and SCG, and Policy code CS are treated as equity funds.

⁵¹The number of distinct funds equals 488 for 1980 to 1989, 1454 for 1990 to 1999 and 2416 for 2000 to 2009.

The turnover ratio is the rate at which the fund changes its stock holdings from year to year and is compiled by the CRSP mutual fund database.⁵² The average turnover ratio is 83.55%. The average fund age is approximately 12 years, and the average number of stocks held by the funds is 99.⁵³ Total load includes the front-end and back-end fees paid by fund investors. The mean total load is 1.25%. This number is small because of a large proportion of non-load funds in our sample.⁵⁴ Other variables are defined and explained in the next section.

III. Empirical Design

In this section, we define the major variables in our study. First, we define the measure of the investment skills or information superiority of mutual funds based on the buy and sell trades of mutual funds. Then we specify how we measure mutual fund returns. The returns are measured against a risk factor model or the stock characteristics-based benchmark. Finally, we illustrate the fund flow variable and introduce three other variables that are used to control for post-earnings announcements drift.

III.1 The measure of the investment skills or information superiority of mutual funds

The measure is motivated by the literature's extensive use of earnings announcement effects to show the informed trading of financial institutions. We use the quarterly holding data to compute this measure of the investment skills or information superiority of mutual funds. The time line for defining the measure is illustrated in Figure 1.

⁵²See Yan and Zhang (2009) for an explanation about turnover in the CRSP mutual fund database.

⁵³The maximum number of stock for our sample is below what is reported in Kacperczyk et al. (2005). This is probably because we use a \$5 price filter.

⁵⁴In the dataset, 51.9% of funds report missing front-load value, and 38.87% funds report missing rear-load value. The mean front load is 2.42% for funds with non-missing observations for the front load, and the mean rear-load is 0.5% for funds with non-missing observations for the rear load. We assign zero for missing values.

Figure 1: Time line for defining the measure

In Figure 1, t is the start date of current quarter, Quarter 0. The measure on t is used to predict the quarterly fund return in Quarter 0 between t and $t+1$. The measure is based on weight change and EAR. The weight change is obtained by comparing the stock holding of two consecutive quarters on $t-2$ and $t-1$. The earnings announcement occurs between $t-1$ and t .

We define the buy trades-based measure in the following way:

$$(1) \quad CAR1_BUY_t = \sum_{j \in \{j: w_{j,t-1} \geq w_{j,t-2}\}} (w_{j,t-1} - w_{j,t-2}) * car1_{j,t-1},$$

where $w_{j,t-1}$ is the weight of stock j in the stock portfolio of this fund on date $t-1$ or at the end of Quarter -1, $w_{j,t-2}$ is the weight of stock j in the stock portfolio of this fund on date $t-2$, $car1_{j,t-1}$ is the 3-day EAR of stock j between date $t-1$ and date t , and $j \in \{j: w_{j,t-1} \geq w_{j,t-2}\}$ means the computation is performed for stocks that are bought by the fund during the period from date $t-2$ to $t-1$. Note that we use the market-return adjusted model to compute the 3-day EAR, and CRSP value-weighted market return is used as the proxy for the market return.

We define the sell trades-based measure in the following way:

$$(2) \quad CAR1_SELL_t = \sum_{j \in \{j: w_{j,t-1} < w_{j,t-2}\}} (w_{j,t-1} - w_{j,t-2}) * car1_{j,t-1},$$

where $j \in \{j: w_{j,t-1} < w_{j,t-2}\}$ means the computation is performed for all the stocks sold by the fund.

Mutual funds are typically long-only investors. Buy trades are likely motivated by the need to invest in undervalued stocks. By contrast, sell decisions may be driven by a need for liquidity. We expect *CAR1_BUY* to be informative, while *CAR1_SELL* may not be informative. We expect positive associations between *CAR1_BUY* and fund returns, while we do not expect associations between *CAR1_SELL* and fund returns. We do not define the measure based on all trades. Even if this measure is informative, the fund return predictability can be attributed to either of the measures we have defined.

Following Kacperczyk et al. (2005), we need to adjust for weight changes that happen as a result of price changes when determining the quarterly buy and sell trades of stocks by mutual funds. Even when stocks are just held and carried over from the last quarter, stock weights can change as a result of stock price changes. Therefore, we will assign a hypothetical weight for each fund quarter. It is calculated in the following way:

$$(3) \quad \tilde{w}_{j,t-1} = \frac{w_{j,t-2} * R_{j,t-2}}{\sum_j w_{j,t-2} * R_{j,t-2}},$$

where $R_{j,t-2}$ is the quarterly return of stock j during Quarter -2, and $\tilde{w}_{j,t-1}$ is the hypothetical weight at the end of Quarter -1. We use $\tilde{w}_{j,t-1}$ in place of $w_{j,t-2}$ for the computation in Equations (1) and (2).⁵⁵

The weight of individual stock within each fund is determined using the holding information from TFN/CDA and the price data from CRSP. We find that the weight change caused by a single fund-stock is, on average, 0.4%, with a standard deviation of 0.7%. The total weight change caused by buy trades in a fund is, on average, 8.2%, with a standard deviation of 20.1% across funds. The mean weight change for sell trades is, on average, -7.8%, with a standard deviation of 19.9%.

⁵⁵We repeat this analysis when the weight change is computed without considering stock price changes, and we find qualitatively similar results.

Table 1 shows that $CAR1_BUY$ is, on average, positive, with a mean of 0.07% and a median of 0.04%. The number is only slightly above zero, and as a result, we refrain from concluding that mutual funds as a whole conduct informed trading. As the focus of our work is to explain the cross-sectional variation in mutual fund informed trading and alpha, it is encouraging to see that $CAR1_BUY$ has a large standard deviation (i.e., 0.54%). We also note that $CAR1_SELL$ is, on average, negative (i.e., -0.04%). The unreported correlation table shows that $CAR1_BUY$ and $CAR1_SELL$ have a weak correlation of -0.09. Therefore, it is not likely that these two measures both represent the investment skills or information advantage of mutual funds. If this were true, we would observe significant correlations.

III.2 Fund performance measures

The main measures of fund performance are derived from the time series of mutual fund return history. These are alphas computed using various risk factor models, including the market model, Fama-French three-factor model, and the Carhart (1997) four-factor model. For the Carhart four-factor model, we run the following regression for fund p in month T using the fund's previous 24-months return data.

$$(4) \quad (R_p - r_f)_t = \alpha_T + b_T \cdot MKT_t + s_T \cdot SMB_t + h_T \cdot HML_t + u_T \cdot UMD_t + \varepsilon_t,$$

$$t = T - 24, T - 23, \dots, T - 1,$$

where $(R_p - r_f)_t$ is the excess return of this fund p over risk-free interest rate in month t , and MKT_t , SMB_t , HML_t , and UMD_t are the market, size, book-to-market and momentum factors, respectively. The estimated factor loadings $\hat{b}_T$, $\hat{s}_T$, $\hat{h}_T$, and $\hat{u}_T$ are then used to compute the Carhart four-factor alpha for fund p in month T ,

$$(5) \quad Alpha4f_{p,T} = (R_{p,T} - r_{f,T}) - (\hat{b}_T \cdot MKT_T + \hat{s}_T \cdot SMB_T + \hat{h}_T \cdot HML_T + \hat{u}_T \cdot UMD_T).$$

If the momentum factor is not included in Equations (4) and (5), we have the Fama-French three-factor alpha (Fama and French (1993)) for fund month (p, T) , which is denoted by $Alpha3f_{p,T}$. Similarly, if only the market factor is specified in Equations (4) and (5), we have the market factor alpha, which is denoted by $Alpha1f_{p,T}$. Summary statistics on the factor model-based fund alphas are provided in Table 1. We find the mean (median) of quarterly $Alpha3f_{p,T}$ and $Alpha4f_{p,T}$ to be -0.23% (-0.30%) and -0.29% (-0.31%) a quarter, respectively. The negative signs of these alphas are consistent with Gruber (1996).

Daniel et al. (1997) propose an alternative set of abnormal performance measures for mutual funds. Instead of using the required return derived using the risk-factor models as the benchmark return, they use the stock characteristics-based benchmark return. Assuming that the stock trades take place at the end of each quarter, their holding-based measures are also meaningful for our study.⁵⁶

Daniel et al. (1997) construct the stock characteristics-based benchmark returns using the returns of 125 passive portfolios. These passive portfolios are formed by triple sorting U.S. stocks using three characteristics: (1) market capitalization, (2) book-to-market ratio, and (3) prior-year return. Then these benchmark returns are assigned to each stock held in the fund portfolio using these three characteristics. As a result, a monthly fund return can be decomposed into three components: (1) characteristics selectivity, (2) characteristics timing, and (3) average style.

Characteristics selectivity measures how well fund managers select stocks that beat stocks with the same characteristics at the beginning of each month. It is defined in the following way:

$$(6) \quad CS_t = \sum_j w_{j,t-1} [R_{j,t} - BR_t(j, t-1)],$$

⁵⁶For example, Kacperczyk et al. (2005) use the characteristics-based measures to show that abnormal returns are the result of the industry concentration in a fund's stock portfolios.

where $R_{j,t}$ is the return on stock j during month t , and $BR_t(j, t - 1)$ is the return on a benchmark portfolio during month t to which stock j was assigned at the beginning of this month according to its size, value, and momentum characteristics.

Characteristics timing measures how well fund managers time the market by tilting portfolios over time towards those stocks with characteristics or styles that have higher returns. It is defined in the following way:

$$(7) \quad CT_t = \sum_j [w_{j,t-1} BR_t(j, t - 1) - w_{j,t-13} BR_t(j, t - 13)],$$

where $BR_{j,t-1}$ is the benchmark return of stock j during month t , and $BR_t(j, t - 13)$ is the benchmark return of stock j 12 months ago. $w_{j,t-1}$ and $w_{j,t-13}$ are the weights at the beginning of this month and 12 months earlier.

Finally, average style captures the returns earned by a fund as a result of the fund's tendency to hold stocks with certain characteristics in the long run. It is defined in the following way:

$$(8) \quad AS_t = \sum_j w_{j,t-13} BR_t(j, t - 13).$$

We obtain the characteristics-based benchmark returns and stock assignments data from Russ Wermers' website. These data are based on Wermers (2004), which is a refined version of Daniel et al. (1997). Summary statistics for the characteristics-based fund measures are provided in Table 1. We find the mean of CS_t , CT_t , and AS_t are 0.22%, 0.08%, and 2.06% a quarter, respectively.

We further discuss these measures in a later section.

III.3 Fund flow and other control variables

Following Zheng (1999) and Kacperczyk et al. (2005), the quarterly fund flow for each fund is defined in the following way:

$$(9) \quad Flow_t = \frac{TNA_t - TNA_{t-1}(1 + R_{t-1}) - MGTNA_{t-1}}{TNA_{t-1}},$$

where R_{t-1} and $MGTNA_{t-1}$ are the fund return in quarter $t - 1$ and the total assets acquired from a merger, respectively. When defining fund flow, we assume new money comes at the end of the quarter. To minimize the impact of outliers in the regression analysis, we set the minimum fund flow per quarter to be -90% and the maximum to be 200%. Obviously if the computed value is less than -100%, the fund flow has no economic meaning. In Table 1, we find that 1 percentile and 99 percentile of quarterly fund flow are -33.86% and 79.86%, respectively.

The measure of the investment skills or information superiority of mutual funds involves EAR; therefore, we make a conscientious effort to control for the well-known effects of the post-earnings announcements drift. The earnings drift was first documented by Ball and Brown (1968), and it is noted by Bernard and Thomas (1990), Bhushan (1994), and Bartov, Radhakrishnan, and Krinsky (2000). The earnings drift is the tendency for stock prices to move in the same direction as EAR. It is generally considered the result of investors' under-reaction to earnings news, and Fama (1998) suggests this financial anomaly is beyond suspicion.

Guided by prior studies on the earnings drift (e.g., Chan, Jegadeesh, and Lakonishok (1996)), we introduce three fund-level measures that act as the control variables for the drift effect. The first variable is the value-weighted average of 3-day EAR for all the stocks in the fund portfolio. It is defined in the following way:

$$(10) \quad CAR1_t = \sum_j^{N_t} w_{j,t} * car1_{j,t-1},$$

where $car1_{j,t-1}$ is the 3-day EAR of stock j in Quarter -1 between date $t-1$ and date t , $w_{j,t}$ is the weight at the beginning of Quarter 0 when fund returns start to be accumulated for the following 3 months, and N_t is the number of stocks held by the fund. In Table 1, we note that, on average, the fund has a positive $CAR1$ of 0.80% and a median value of 0.65%.⁵⁷

⁵⁷Note that this is the fund-level $CAR1$ computed using the Q-0 (quarter end) weight and the earnings announcement return between Q-1 and Q-0 as in illustrated in Figure 1. If the weight is before the event at

The second variable is the earnings surprise at the fund level. Again, we need to measure the earnings surprise for the individual stocks first and then aggregate it to the fund level. Following Livnat and Mendenhall (2006), we specify the earnings surprise for the individual stock j in Quarter -1 in the following way:

$$(11) \quad sur_{j,t-1} = Dec\left(\frac{eps_{j,t-1} - eps_{j,t-5}}{P_{j,t-1}}\right),$$

where $eps_{j,t-1}$ and $eps_{j,t-5}$ are the reported earnings of stock j in Quarter -1 and Quarter -5 , respectively; $P_{j,t-1}$ is the stock price when the earnings announcement is made in Quarter -1 , and $Dec(\cdot)$ means we transform the raw value of earnings surprise into quarterly decile ranks. These transformations are also found in Bernard and Thomas (1990), Bhushan (1994), and Bartov et al. (2000).⁵⁸ As a result, the fund level earnings surprise can be computed in the following way:

$$(12) \quad SUR_t = \sum_j^{N_t} w_{j,t} * sur_{j,t-1}.$$

The final control variable for the drift effect is adapted from $CAR1_t$. Berkman, Dimitrov, Jain, Koch, and Tice (2009) suggest that EAR can be noisy in the sense that stock mispricing is often corrected by the public disclosure of earnings. We focus on the direction of EAR and define it in the following way:

$$(13) \quad Dnews1_t = \sum_j^{N_t} w_{j,t} \cdot sign(car1_{j,t-1}),$$

where $sign(\cdot)$ is the sign function and will take a value of 1 if $car1_{j,t-1}$ is positive and 0 if it is negative.

Q-1, the definition is similar to Baker et al. (2010), yielding a mean of 0.27% and a median value of 0.20% for our sample. In fact, the numbers are comparable to Table 3 in Baker et al. (2010). Their yearly alphas from 1984 to 2005 are averaged quarterly to be 0.16%.

⁵⁸We use the raw value of earnings before decile transformation as the control variable. The results are qualitatively the same. We try an alternative measure to SUR using the standard deviation as the denominator instead of the stock price. This also does not affect our main results. These tables are available on request.

IV. Empirical Analysis

In this section, we use both the regression and portfolio approaches to show the fund return predictability of the measure of the investment skills or information superiority of mutual funds. We then show that this measure is persistent. We conduct some additional tests to ensure that the return predictability of the measure is not the result of earnings drift. Overall, our results suggest that fund managers possess different skills or information advantages that result in different fund performance.

IV.1 Regression analysis

In this subsection, we perform the quarterly Fama-French regression (Fama and MacBeth (1973)) of fund returns on the measure of the investment skills or information superiority of mutual funds from 1984 to 2009. The fund-return measures are based on the risk-factor models. We analyze *CAR1_BUY* and *CAR1_SELL* separately in the regressions. This type of regression is run to isolate the effect of the measure on fund return from other factors known to affect fund returns. The following is a typical regression model:

$$(14) \quad Ret_{t+1} = a + b \cdot CAR1_BUY_t + c \cdot fund_char_t + d \cdot drift_control_t + \varepsilon_t,$$

where Ret_{t+1} is the one-quarter ahead fund return, and $fund_char_t$ is a list of fund characteristics, including the log size of the fund, expense ratio, fund turnover, the log of fund age, total load, and fund flow in the previous quarter.⁵⁹ To address the concern that our results may be driven by post-earnings announcement drift, we also control for the fund-level EAR, $CAR1_t$, the fund-level earnings surprise decile ranks, SUR_t , and the fund-level EAR direction, $Dnews1_t$.

Table 2 is about here.

⁵⁹The fund characteristics variables follow Cremers and Petajisto (2009), Massa and Patgiri (2009), and Yan (2008). The fund age is defined as the number of years since the fund was first offered to the public.

Panel A of Table 2 shows the results of the Fama-MacBeth regressions. As shown in Column 1 to Column 8, the measure *CAR1_BUY* is significantly and positively related to future fund returns. The R^2 across all the specifications is, on average, 5%. The relationship holds when the fund return is measured by *Alpha3f* and *Alpha4f*. The standardized parameter estimates for these quarterly regressions are not tabulated but they are available on request.⁶⁰ We find that one standard deviation change in *CAR1_BUY* produces a 10 basis point change in *Alpha3f* and an 8 basis point change in *Alpha4f* across the funds.

Panel A shows that *TNA* is negatively related to fund returns. This confirms the dis-economy of scale in fund management, examined by Berk and Green (2004), Chen et al. (2004), and Yan (2008). *EXP_RATIO* is significantly related to fund returns as well, which is consistent with Carhart (1997), who finds net fund returns are negatively correlated to expense levels. The coefficient before *TURNOVER* is positive but non-significant when the fund return is measured by *Alpha3f*. *AGE* is negatively related to fund returns, which is consistent with Table V in Kacperczyk et al. (2005). *TOTAL_LOAD* is negatively related to fund returns. The negative associations of both the expense ratio and total load with fund returns are consistent with the puzzle documented by Gil-Bazo and Ruiz-Verdú (2009), who find that funds with worse before-fee performance charge higher fees. *FLOW* is positively related to fund returns, supporting the smart money effect documented by Zheng (1999).

CAR1 is positively related to fund returns measured by *ALPHA3F*. In other cases, however, the three control variables for the post earnings announcement drift are not significantly related to fund returns. At the fund level, the earnings surprises decile ranks, *EAR*, and *EAR* directions do

⁶⁰This is achieved by standardizing the explanatory variables first and then running quarterly Fama-MacBeth regressions.

not predict future returns.⁶¹ The regression result suggests that *CAR1_BUY* contains more information than earnings surprises, *CAR1*. This is interesting because by construction *CAR1_BUY* and *CAR1* must be highly correlated. Unreported statistics shows the correlation between them is as high as 0.3.

Panel B of Table 2 shows the results of quarterly Fama-MacBeth regressions of fund returns on *CAR1_SELL*. *CAR1_SELL* is negatively related to fund returns. However, the relationships are insignificant. From the results shown in this panel, we conclude that sell trades are not useful for predicting future fund returns. As we suggested earlier in this study, sell trades are not as informative as buy trades. Therefore, all subsequent analysis focuses on the measure *CAR1_BUY*.

IV.2 Portfolio analysis

We sort all the sample funds from 1984 to 2009 into 10 portfolios according to the measure of the investment skills or information superiority of mutual funds at the start of each quarter. The funds are equally weighted in the portfolios to ensure the results are not influenced by fund size. We then collect the one-quarter ahead quarterly raw returns as well as the risk factor model-based performance measures for the mutual funds. Note that the fund returns are after fund expenses, and the 10 portfolios are rebalanced quarterly.

Table 3 is about here.

Table 3 shows the results of the above portfolio analysis. Note that the raw returns for various groups of mutual funds are positive, but the returns become negative after controlling for the risk factors. This is consistent with Gruber's (1996) finding that the average mutual fund underperformed passive market indexes by approximately 65 basis points a year from 1985 to 1994.

⁶¹We replicate the drift study and tabulate the results in Table A1. In fact, we only find the drift effects for equally weighted portfolios. We do not find drift effects for value-weighted portfolios, which is consistent with the finding in Table 2.

As shown in Table 3, the fund returns gradually increase with the portfolio decile ranks, confirming the fund-return predictability of the measure $CAR1_BUY$. The decile 10 funds with the highest value of $CAR1_BUY$ earn raw returns of 2.14% a quarter after expenses, which is 47 basis points higher than decile 1 funds. When the systematic risks are considered, the return difference between the two groups of funds is still statistically significant. The return differences are 52, 47 and 37 basis points a quarter for the market model alpha ($Alpha1f_{p,T}$), the Fama-French three-factor alpha ($Alpha3f_{p,T}$) and the Carhart four-factor alpha ($Alpha4f_{p,T}$), respectively. Comparison between the bottom and top quintile or the bottom and top half leads to similar conclusions. In addition, the return spread is not simply the result of extreme returns to either the top or bottom decile funds.

IV.3 Persistence of the measure

In this subsection, we analyze the persistence of the measure. The measure $CAR1_BUY$ is a proxy for the investment skills or information superiority of mutual funds. Though investment skills evolve over time, we expect different fund managers to have different skills. Also, the information advantage of mutual funds is firm specific. Therefore, we expect mutual funds in our sample to show persistence with respect to the measure.

There is some debate about persistence in mutual fund performance. Carhart (1997) shows that after controlling for stock momentum, the well-documented persistence in mutual fund performance does not exist. Busse, Goyal, and Wahal (2010) examine domestic equity institutional products managed by 1,448 investment management firms between 1991 and 2008 and find only modest evidence of persistence in three-factor models and little to none in four-factor models. On the other hand, some studies show that there are some fund managers who are truly skilled. For instance, Kosowski et al. (2006) show that a sizable minority of fund managers persistently earns superior alphas. These researchers conduct a bootstrap statistical analysis and

find these managers' performance is not the result of luck. Barras, Scaillet, and Wermers (2010) and Fama and French (2010) also suggest the skills of some funds result in better performance. Kacperczyk et al. (2008) show that the unobserved actions of some funds persistently create value. In our study, we hold that the skills or information advantage captured by the measure may be persistent, even though mutual fund performance may not be persistent. Total fund return is exposed to systematic risk factors and there is no guarantee of persistence. In fact, Titman and Tiu (2011) show that better-informed hedge funds choose to have less exposure to factor risk.

First, we examine whether the level of the measure persists for some quarters. In particular, we sort the funds into 10 groups by *CAR1_BUY* in a quarter and then compare the measure level across the 10 fund portfolios in the subsequent four quarters. If the measure is persistent, we may observe that the fund portfolio with larger *CAR1_BUY* in the first quarter continue to have larger *CAR1_BUY* in the following four quarters.

Table 4 is about here.

Table 4 shows the results of the above portfolio analysis. The fund portfolio-level measure of *CAR1_BUY* is the simple average of the measures from all the composite funds. As *CAR1_BUY* may be a noisy measure, we delete the top and bottom 1% observations in each quarter. We find that in three out of the following four quarters, top funds continue to have larger values for *CAR1_BUY*. For the immediate next quarter, the difference between top and bottom deciles, top and bottom quintiles, and top and bottom halves is statistically significant at the 1% level.

Figure 2 is about here.

Figure 2 reinforces the test shown in Table 4. In this figure, we show the average decile rank values for *CAR1_BUY* for the 10 fund portfolios from eight quarters before and eight quarters after portfolio formation. In each quarter, we rank the funds into deciles by *CAR1_BUY*. We then collect the rank values for each fund in the prior eight quarters and the subsequent eight quarters.

The portfolio-level decile rank values of *CARI_BUY* are the simple average of the composite funds' decile ranks. Figure 2 shows the decile 10 funds, the most skilled or informed group of mutual funds, are highly persistent. It is also the case for other groups of funds with relatively large *CARI_BUY* (e.g., decile 8 funds).

Finally, we use past information about *CARI_BUY* to predict future fund return. Mutual funds' investment skills or information advantages are arguably persistent. If the measure *CARI_BUY* is able to capture these two features, then past information about this measure will also predict future fund returns. Table 5 shows past information about *CARI_BUY* is able to predict future fund returns.

Table 5 is about here.

In Panel A of Table 5, we regress the fund return measured by *Alpha3f* and *Alpha4f*, respectively, on the measure of the previous four quarters. We find that the measures of the past are positively associated with fund returns. This relationship is significant when the measure of Quarter -1 is used and the fund return is measured by *Alpha3f*. The relationship is also significant when the measure of Quarter -4 is used and the fund return is either measured by *Alpha3f* or *Alpha4f*.

We construct two new variables, *AVG_CARI_BUY* and *AVGRANK_CARI_BUY*, for each fund quarter. This is the average of *CARI_BUY* and its decile rank in the previous four quarters (i.e., from Quarter -4 to Quarter -1). The calculation of these two new variables does not involve the current quarter's *CARI_BUY*. We find that these two variables are also significantly and positively associated with fund returns.

Confirming our conjecture, past information about *CARI_BUY* successfully predicts future fund returns. In fact, the relationship is larger and more significant compared to the use of *CARI_BUY*. This is not too surprising. The quarterly measure *CARI_BUY* is noisy, and the average version of

it would be less noisy. To address the concern that our newly created measures just capture the fund momentum effect from the past, we control for the lagged abnormal fund returns in Panel B of Table 5. We find the coefficient before the lagged fund performance measure is significantly positive, confirming the well-documented persistence in mutual fund performance.⁶² As a result of introducing lagged fund return, the significance of the measure becomes weaker. This is not puzzling because the lagged abnormal fund return could also proxy for a fund's investment ability. As these results show, the measure is still significant, and the magnitude of the coefficient is not significantly smaller.⁶³

IV.4 Decomposition of buys into first buys and non-first buys

We are interested in knowing which buy trades are most informative. Baker et al. (2010) suggest that first buys are a good indication of skilled trading by mutual funds. Following their suggestion, we decompose buy trades into first buys and non-first buys. If the stock is not owned in the previous quarter and is now owned by a fund, then this stock is a first buy stock. We define the measure of the investment skills or information superiority of mutual funds based on first-buy trades in the following way:

$$(15) \quad CAR1_{FB} = \sum_{j \in \{j: w_{j,t-1} > 0, w_{j,t-2} = 0\}} w_{j,t-1} * car1_{j,t-1},$$

where $w_{j,t-2} = 0$ means the stocks are first buys.

We define the measure of the investment skills or informational superiority of mutual funds based on non-first-buy trades in the following way:

$$(16) \quad CAR1_{nonFB} = \sum_{j \in \{j: w_{j,t-1} \geq w_{j,t-2}, w_{j,t-2} \neq 0\}} w_{j,t-1} * car1_{j,t-1},$$

where $w_{j,t-2} \neq 0$ means the stocks are non-first buys.

⁶²See Carhart (1997) for studies on fund performance persistence.

⁶³We conduct a parallel analysis on *CARI_SELL* and do not find return predictability. This confirms our previous assertion that sell trades are not as useful for predicting fund returns as buy trades.

By definition, $CAR1_BUY$ is the sum of $CAR1_FB$ and $CAR1_nonFB$. The proportion of the first-buy trades out of the total buy trades is 38%.⁶⁴ We find that the mean for $CAR1_FB$ is 0.04% compared to the 0.07% shown in Table 1. In addition, the correlation between $CAR1_nonFB$ and $CAR1_FB$ is only 0.04.

Table 6 is about here.

Table 6 shows the results of the regressions run for the two newly defined measures. The sample size differs across the columns. This is because there are no first buys in some fund quarters. From the first two columns, we find that the first buys-based measure is informative when the abnormal fund return is measured by $Alpha3f$ and $Alpha4f$. In contrast, the non-first buys are not informative. We then use past information about $CAR1_FB$ and $CAR1_nonFB$, and compute the average decile rank for these two variables in the past four quarters. We find that past information about $CAR1_FB$ predicts future fund returns. As for the non-first buys-based measure $CAR1_nonFB$, the relationship is significant only when the fund return is measured by $Alpha3f$.

The finding about the measure based on first buys is consistent with Baker et al. (2010). It suggests that mutual funds do carry out informed trading because first buys are clear intentions of buying stocks. Therefore, the analysis in this subsection supports the validity of $CAR1_BUY$ as a measure of the investment skills or information superiority of mutual funds.

IV.5 Characteristics-based measures of fund performance

Even though the measure of $CAR1_BUY$ is based on trades, the characteristics-based measure of fund performance developed by Daniel et al. (1997) may also suit our analysis. Assuming that the trades take place at or near the end of each quarter, fund performance measures derived from quarterly stock holdings are also suitable. The analysis using these measures reveals the sources of

⁶⁴We find the number of fund-quarter first-buy stock is 1,927,507, and the total number of fund-quarter buys is 5,131,273. The mean weight change is 0.7% for first buys and 0.4% for all buys.

mutual fund alphas. In particular, CS measures the stock-selection skills of mutual funds because they buy stocks that are undervalued. CT shows how well a mutual fund times the market and buys stocks with the right characteristics when these characteristics produce high returns. AS attributes fund returns to the general fund style. We obtain the benchmark return and stock assignments data from Russ Wermers' website and compute the characteristics-based measures of fund performance for our sample funds from 1984 to 2009.

When decomposing stock returns into CS, CT and AS, we determine the stock weight based on all the stocks with available characteristics benchmark returns. We find that the average abnormal performance during our sample period is comparable to the performance reported by Kacperczyk et al. (2005) from 1984 to 1999. The summary statistics in Table 1 show that the mean CS measure for our sample funds is 0.66% a year, while the annualized average CS measure shown in Kacperczyk et al.'s (2005) Table III is 0.80%.

Table 7 is about here.

Table 7 shows results of a portfolio analysis when fund performance is measured by the characteristics-based measures. First, Panel A shows our decomposition of fund return is proper. By definition, the sum of CS, CT and AS is the pre-expense raw return of each fund. Adding together the three measures for each decile fund portfolio in this table yields numbers close to the average raw returns shown in Table 3. Second, as we expect, the funds with a higher value for *CAR1_BUY* shows stronger stock-selection skills. Those funds earn higher CS returns. The return spread between the top and bottom decile funds is 41 basis points a quarter, which is about the same abnormal return spread documented in Table 3. We find that *CAR1_BUY* is not significantly related to the market-timing skills of mutual funds measured by CT. We also find that *CAR1_BUY* is not related to AS, which is the long-term tendency of mutual funds to adopt certain styles and is not supposed to be captured by our quarterly measure.

Stocks held by the fund are classified into positive and negative EAR stocks according to the most recent EAR. Total fund returns are produced by adding positive and negative EAR stocks. We further divide fund returns measured by CS into positive and negative EAR regions. If the return predictability of *CAR1_BUY* is not about the earnings drift and is about investment skills or information advantages, the measure will predict fund winners in both regions. Indeed, Panel B shows that the measure is positively associated with fund returns that are generated separately by positive and negative EAR stocks.

In Panel C of Table 7, we run the quarterly Fama-MacBeth regression of fund return measured by CS on the measure and other fund characteristics from 1984 to 2009. We confirm the results of all the preceding univariate analysis and find that *CAR1_BUY* is associated with the stock-selection skills of mutual funds. The result in Panel C is striking as all the other variables are insignificantly related to CS.⁶⁵

IV.6 Return predictability when a post-earnings announcement drift factor is introduced

In this subsection, we evaluate whether the measure still has return predictability when post-earnings announcement drift is factored in the fund return. Chan et al. (1996) find that earnings momentum and price momentum are related but do not subsume one another. Therefore, it is worthwhile to add another risk factor to the Carhart four-factor model. Following Kim and Kim (2003), we create a monthly factor representing the risk of unexpected earnings surprises. We use the 3-day EAR as the measure of earnings surprises. In each month, we sort all the stocks in CRSP and COMPUSTAT into six equally weighted portfolios by size (i.e., big and small) and unexpected earnings surprises (i.e., EAR-L, EAR-M, and EAR-H). The monthly factor is then the

⁶⁵We use EAR as the fourth firm characteristics and refine the computation of the fund return measure CS. The unreported results are qualitatively similar.

simple average of return differentials between EAR-H and EAR-L stocks in each of the two size groups. We denote such a risk factor as *EA* and run the following regression:

$$(17) \quad (R_p - r_f)_t = \alpha_T + b_T \cdot MKT_t + s_T \cdot SMB_t + h_T \cdot HML_t + u_T \cdot UMD_t + e_T \cdot EA_t + \varepsilon_t, \\ t = T - 24, T - 23, \dots T - 1.$$

The factor-loading estimate from this regression for each fund month is then used to compute the five-factor alpha in a way similar to Equation (5). We denote this fund performance measure as *Alpha5f*. We then run the quarterly Fama-MacBeth regression of these fund returns on the measure and other fund characteristics. The results are shown in Table 8.

Table 8 is about here.

Table 8 shows that the measure is significantly related to the fund return measured by *Alpha5f* across the board. Compared to the results in Table 2, the additional control of earnings drift in the fund return shown in Column 1, Table 8 appears to reduce the statistical significance of the fund-flow coefficient. This is consistent with Sapp and Tiwari's (2004) suggestion that the smart money effect can be explained by the stock momentum effect. Also compared to Table 2, the coefficient before TNA becomes more significant, showing diseconomies of scale in money management.

IV.7 The effect of investment styles on the return predictability

Daniel and Titman (1999) in their Table 1 show that momentum effect is much stronger among growth stocks (with low BM ratio) than value stocks. Psychological studies (e.g., Einhorn (1980)) show that investors are more overconfident in situations when feedback on their information or decisions is slow or inconclusive than when feedback is clear and rapid. Daniel, Hirshleifer and Subrahmanyam (1998) propose a theory of attribution bias and posit that the momentum effect should be stronger for growth stocks. Investors overweigh information that confirms their valuation and underweigh information that does not confirm their opinions. These delayed overreactions produce a momentum effect that is stronger for growth stocks.

By definition, high *CAR1_BUY* funds have just bought into stocks that reports unexpected high earnings. These funds are in a better position to reap momentum benefits than other funds. Superior returns to high *CAR1_BUY* funds may simply result from momentum effect. If this is true and the momentum effect is stronger among growth stocks, we expect the measure to have a high return predictability for growth funds. On the other hand, if superior returns are brought about by the managerial skill or information advantage captured by *CAR1_BUY*, we do not expect that a high return predictability for growth funds. On the contrary, we hypothesize that predictability is higher for value funds.

CAR1_BUY is based on the idea that mutual funds buy stocks they believe are undervalued. Reported earnings and the associated announcement returns are perhaps more relevant for value stocks than growth stocks. It follows that the measure based on the trade of growth stocks is less successful than the measure based on the trade of value stocks. In other words, the earnings announcement effect does not indicate informed trading when mutual funds are in the market for undervalued growth stocks. The measure is, therefore, less useful for capturing investment skills or information advantages for growth funds, and we expect the return predictability of the measure to be weaker for growth funds than for value funds.

We classify our sample funds into growth funds and value (non-growth) funds using two methods. In the first method, we use the investment code of each mutual fund provided in the CRSP Mutual Fund database to divide our sample funds into growth and value funds. We mainly use strategic insights objective (SI) Codes AGG and GRO to identify the growth funds. When the SI code is missing, we use the Lipper codes ELCC, G, LCCE, LCVE, MLCE, MLVE, SP, SPSP, LCGE, and MLGE to identify growth funds. With this method, we identify 33,850 growth-fund-quarters out of the 81,352 fund-quarters from 1984 to 2009. In the second method, we identify a growth fund using the fund's stock holding's book-to-market ratio. If the average BM ratio is low, then the fund is considered a growth fund. We obtain the book-to-market ratio for all stocks from Russ

Wermers' website. Then we calculate the weighted average of the log BM ratio of the stocks that are held for each fund quarter and split the sample into two halves by using the median log BM ratio. We note that these two methods are related. The median book-to-market value for the growth funds identified by the first method is 0.42, which is less than the median value of 0.49 for the value funds. The two sets of growth dummies created by these two methods have a correlation coefficient of 0.20, which is significant from zero.

Using the investment codes to identify the growth funds, we find that the mean (median) value of *CAR1_BUY* for a growth-fund quarter is 0.056% (0.038%) and the standard deviation is 0.56%, while the mean and median value of *CAR1_BUY* for a value-fund quarter is 0.073% (0.047%) and the standard deviation is 0.52%. Using the quarterly fund-level log BM ratio as the identifier, the mean (median) value of *CAR1_BUY* for a growth-fund quarter is 0.076% (0.048%) and the standard deviation is 0.58%, while the mean and median value of *CAR1_BUY* for a value-fund quarter is 0.066% (0.042%) and the standard deviation is 0.51%. It appears that *CAR1_BUY* is similar among growth and value funds.

Table 9 is about here.

We use the Fama-MacBeth regression to analyze the effect of investment styles on the fund return predictability of *CAR1_BUY*. Panel A of Table 9 shows the investment codes used to identify the growth and value funds. From Column 1 to Column 3 of this panel, *CAR1_BUY* has no return predictability for the growth funds. On the other hand, Column 4 to Column 6 show that *CAR1_BUY* has a strong return predictability for the value funds. This finding supports our hypothesis that the return predictability of the measure should be higher for value funds than for growth funds. The return predictability of the measure is not the result of earnings drift. If that was the case, growth funds' returns should be more associated with the measure.

In Panel B, we use the fund-level log BM ratio to identify growth funds, and the findings are similar. In unreported results, we show that the weaker predictability for growth funds is not the result of the non-linearity between the measure and the fund return. When we include the square term of the measure in the regression, we see a positive but insignificant square term, and the results for the growth-style effect remain qualitatively the same.

IV.8 Sub-period analysis

In this subsection, we conduct sub-period analysis to examine whether the results are robust to various sub-periods. In addition, we are interested in knowing the effect of Regulation FD (Reg FD) on the fund-return predictability of the measure. Reg FD has been in place since October 2000. Before Reg FD, firms could selectively disclose non-public information to a few securities analysts and institutional investors, giving them an unfair information advantage. Reg FD was designed to prevent these unfair practices. Ke, Petroni, and Yu (2008) find that Reg FD may have stopped selective disclosure behavior and changed the trading pattern of transient institutions. Reg FD could have a negative effect on the measure's ability to predict fund returns if this ability to predict fund returns is the result of an information advantage obtained from selective disclosure.

Table 10 is about here.

We divide the sample periods into three sub-periods: (1) 1984 to 1992, (2) 1993 to 2000, and (3) 2001 to 2009. We run the quarterly Fama-MacBeth regression in the three sub-samples and report the results in Table 10. From 1984 to 1992, there is no evidence that the measure predicts fund returns. From 1993 to 2000, the measure is significantly linked to fund returns. From 2001 to 2009, with Reg FD in effect, we find an even stronger link between the measure and fund return. These findings suggest that the measure captures the investment skills of fund managers and their ability to interpret public news. If the measure is about the information advantages of these funds, these information advantages are not the result of selective disclosure.

IV.9 Stock performance evidence

In this subsection, we provide stock performance evidence for the fund-return predictability of the measure *CARI_BUY*. If mutual funds are informed traders and are good at selecting stocks, the stocks held by informed funds will realize larger returns in the future, regardless of their recent earnings surprises. In other words, larger stock returns reflect the sound judgments of top mutual funds.

The analysis involves all the stocks held by the sample funds from 1984 to 2009. A stock in a calendar quarter can be held by multiple funds. Therefore, the mean value of *CARI_BUY* for all the mutual funds currently holding this stock is used as a measure of investor sophistication. It is also called the stock under-value score and measures the sophistication or information advantage of the investor base. Note that different funds hold different amounts of the same stock. The stock under-value score is the value-weighted average of *CARI_BUY* for all the funds holding the stock.

After we obtain the stock under-value score, we sort stocks into quintiles using this score at the start of each quarter. We also independently sort stocks into three groups by their most recent EAR. As a result, 15 equally weighted stock portfolios are formed for each quarter. We measure abnormal stock-return using Daniel et al.'s (1997) measure: that is, the raw stock return minus the characteristics-benchmark return. We collect one-quarter ahead abnormal returns for the 15 stock portfolios.

Table 11 is about here.

Panel A of Table 11 contains the results of the above analysis. We confirm the existence of earnings drift because high EAR stocks earn larger returns than low EAR stocks. More important, we find that among stocks with medium EAR (tercile rank 2) stock returns are higher with larger under-value scores: that is, when the investor base is more sophisticated or informed. The returns to the top-score quintile stocks are 34 basis points more than the bottom stocks. The fact that the

under-value score does not have any stock return predictability for low (tercile rank 1) or high EAR stocks (tercile rank 3) suggests that our fund measure's power to predict future fund returns is not driven by earnings drift.

The quarterly fund measure *CAR1_BUY* can be noisy. Therefore, in Panel B, we obtain the stock under-value score by taking the value-weighted average of *AVGRANK_CAR1_BUY* for all the mutual funds holding the stock. *AVGRANK_CAR1_BUY* is defined in the same way as in Table 5. It is based on past information about *CAR1_BUY* and is the simple average of decile rank of this measure in the previous four quarters (not including the current quarter). We again find larger returns for stocks whose investor base is more sophisticated or informed. The return spread between the top and bottom quintile stocks is significant among stocks with low and medium EAR.

Overall, we find that stocks held by high *CAR1_BUY* funds realize larger returns, regardless of their recent EAR. This finding suggests that top mutual funds are informed and can select undervalued stocks, and the fund return predictability of the measure is not likely a result of earnings drift.

IV.10 Analysis using the monthly file

Note that all the analysis before this sub-section uses *ALPHA3F* or *ALPHA4F*. These are conditional alphas in asset-pricing factor models, and they are estimated using the previous 24-months fund return data. In this subsection, we use a monthly version of the sample from 1984 to 2009 and evaluate the return predictability of *CAR1_BUY* using the unconditional alphas. The analysis shows whether the predictability is robust to the use of unconditional alpha as a fund return metric. Note also that the sample includes the quarterly and semi-annually disclosing funds, and as a result, it mimics true fund investment scenarios.

The total fund-month observation in the monthly file from 1984 to 2009 is 309,350.⁶⁶ Each month we sort the funds into 10 equally weighted portfolios by *CAR1_BUY*. We compute the sample mean return for each fund portfolio. We also compare alphas between fund portfolios. Specifically, for each of the 10 portfolios, the whole time series of returns are projected to risk factors. The resulting alphas from the 10 projections are then compared. Note that these alphas are computed using the whole return history and, therefore, is unconditional. We use the market, Fama-French three-factor, and the Carhart four-factor models to compute the alphas.

Table 12 is about here.

Table 12 gives us the unconditional alphas for the above monthly fund portfolios from 1984 to 2009. We note that the return spread between the top and bottom fund portfolios is significant in all the four columns. In terms of raw return, the market model alpha and the Fama-French three-factor alpha, the portfolio's returns generally increase with the decile ranks of *CAR1_BUY*. When the Carhart four-factor alpha is used, the return difference is not obvious among fund portfolios from decile 2 to 10. However, the return is extremely low for the decile 1 fund portfolio, resulting in the significant return spread between top and bottom fund portfolios.

IV.11 Simulated mutual funds

In this subsection, we simulate 1,200 mutual funds from 1984 to 2009. If the measure is not about fund skills or information advantage but about earnings drift, then the measure will have return predictability among these funds.

The simulation technique follows Kothari and Warner (2001). In the first month, a portfolio is constructed by randomly choosing 100 stocks from the pool of all U.S. stocks.⁶⁷ The probability choice can be proportional to the market size or simply equal across stocks. Obviously, equal

⁶⁶The number is larger than three times the observation of the quarterly file in Table 2. This is because for each semi-annually disclosure fund quarter, there is only one quarterly observation in Table 2 but six monthly observations in the monthly file here.

⁶⁷The determination of this type of pool follows Fama and French (1992).

probability favors the selection of small stocks. To approximate the sample statistics of our sample funds, we require a 10% monthly turnover rate. That is, starting from the second month, 10 stocks are sold, and 10 new stocks are bought.⁶⁸ The exact number of shares bought is then the total number of shares outstanding for the firm multiplied by a random number.⁶⁹ This procedure is repeated 1,200 times. For these funds, monthly CS return and the quarterly *CAR1_BUY* measure are computed.

Table 13 is about here.

Table 13 shows the results of a portfolio analysis of these 1,200 simulated funds. In Column 1, stocks are randomly chosen with an equal probability. In Column 2, stocks are randomly chosen with a probability proportional to firm size. The measure *CAR1_BUY* is calculated for each simulated fund quarter. At the start of each quarter, we sort the funds into 10 portfolios using *CAR1_BUY* and collect the equally weighted fund return for each portfolio during this quarter.

Note that the monthly fund return is the value-weighted abnormal return adjusted for stock characteristics of all the stocks held at the start of the month. Unreported quarterly raw returns are on average 3.5% for Column 1 and 3.2% for Column 2. These two numbers are plausible because the monthly return for the equally weighted CRSP index is 1.03% and 0.91% for the value-weighted index from 1984 to 2009.⁷⁰ More important, we do not find that the measure predicts fund winners in the 1,200 simulated mutual funds. This finding suggests that the return predictability uncovered in our previous analysis is not the result of earnings drift but the result of trading decisions of fund managers.

IV.12 Comparison with other measures of fund skills

⁶⁸We tried a 20% monthly turnover ratio and the results were similar.

⁶⁹In the sample, the fraction of shares owned by a fund is, on average, 0.15%, with a standard deviation of 0.25%. To ensure a positive fraction, we use the corresponding log-normal function. Note that in this way we are, in fact, computing value-weighted returns for simulated stock portfolios.

⁷⁰Our sample stocks yield returns slightly higher than the index, and this is probably the result of the \$5 dollar filter we used and the survivorship bias.

In this subsection, we compare the measure *CARI_BUY* with other measures of fund skills in the literature in the regression setting. One of those measures is the fund skill measure also motivated by Baker et al. (2009) in Wermers et al. (2010) (See their Appendix C for details).⁷¹ Therefore, their measure is conceptually the same as ours. In fact, their measure is shown to be the sum of *CARI_BUY* and *CARI_SELL* multiplied with a constant number specific to each fund.⁷² Previously, we have shown that *CARI_BUY* is informative, and *CARI_SELL* is negatively related to fund return. It is yet to see if the measure of Wermers et al. (2010), which we denote as *WEAR*, is related to fund returns.

The other measures are as follows: *SIM* is a fund skill measure motivated by Cohen, Coval, and Pastor (2005) in Wermers et al. (2010), capturing the idea that stocks are of high quality as other skillful funds also hold them; *RETGAP* is the return gap measure from Kacperczyk, Sialm, and Zheng (2006); *ICI* is the industry concentration index of Kacperczyk, Sialm, and Zheng (2005); *ACTIVESHARE* is the measure of deviation of fund holding from the benchmark index in Cremers and Petajisto (2009).⁷³

Table 14 is about here.

Table 14 reports the regression results. We use the control variables as in Column 5 of Table 2. In Table 14, the measure of Wermers et al. (2010) is not informative about future return. It is negatively related to fund return once it is used together with the measure *CARI_BUY*. This confirms our findings about *CARI_BUY* and *CARI_SELL* in previous sections. *SIM* is positively related to fund return but insignificantly both when used alone and together with *CARI_BUY*. *RETGAP* is significantly and positively related to fund performance. *CARI_BUY* is not significant when used with *RETGAP*. This is perhaps due to a smaller sample with valid *RETGAP*

⁷¹ Our first version is earlier than Wermers et al. (2010). Their prior versions did not mention the work of Baker et al. (2009).

⁷² This constant number is $1/\sum_{j \in \{j: w_{j,t-1} \geq w_{j,t-2}\}} (w_{j,t-1} - \tilde{w}_{j,t-2})$. It is larger for funds with higher turnover.

⁷³ *RETGAP* and *ACTIVESHARE* are downloaded from the website of Review of Financial Studies and Antti Petajisto, respectively. All the other measures are calculated by us.

observations. The coefficient before *ICI* is significantly positive, whereas the coefficient before *ACTIVESHARE* is not significant. Unreported tests for *ACTIVESHARE* using the same sample period of 1992 to 2003 as in Cremers and Petajisto (2009) do find that *ACTIVESHARE* is significantly and positively related to fund return. Finally, when we put all the measures together, we find *CARI_BUY*, *SIM* and *ICI* are significantly and positively associated with fund return. The coefficients before *WEAR* and *ICI*, and *ACTIVESHARE* are insignificant in this smallest sample from 1990 to 2006.

V. Conclusion

Many studies in the finance and accounting literature use EAR effects to show informed trading of financial institutions. Motivated by these studies, we use a measure to represent the investment skills or information superiority of mutual funds based on their buy trades. From 1984 to 2009 in the context of decile portfolios, the top fund portfolio outperforms the bottom fund portfolio by 47 basis points per quarter.

We find this measure significantly relates to fund returns, controlling for other fund characteristics and earnings drift in regressions. The relation holds particularly well after the introduction of Regulation FD. We also find that lagged measures are useful in predicting fund return, and predictability is robust to the control of lagged fund alpha. This finding, together with other tests, shows that this measure is persistent.

We conduct a few tests to show that the finding is not about earnings drift. First, we construct a systematic risk factor for earning drift to calculate the abnormal fund return. The measure still predicts such fund returns. Second, we divide the sample into growth and value funds and find strong fund-return predictability for value funds and not for growth funds. Third, we find that stocks held by skilled funds earn larger returns in the future, regardless of their recent EAR.

Fourth, we simulate 1,200 mutual funds from 1984 to 2009 and do not find the measure predicts returns among these funds.

Our study has limitations though. We know very little about the nature of the fund skills represented by this measure. For example, is this measure associated with market timing? In future studies, we should examine the determinants of this measure. It is also interesting to examine in more detail how fund persist in terms of this measure.

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Table 1: Summary Statistics

This table contains summary statistics for our sample. RET_{t+1} is one-quarter ahead fund return as a percentage. TNA is the total net asset under management. EXP_RATIO is the total expense divided by the fund assets. $TURNOVER$ is the fund's stock holding turnover rate provided by CRSP. AGE is the number of years since the fund was first offered to the public. $NUMSTOCK$ is the number of stocks that are held at the fund quarter. $TOTAL_LOAD$ is the total load charged by the fund. $FLOW$ is fund flow in the previous 3 months. $CARI_BUY$ is the measure of investment skills or information superiority for a fund based on its buy trades. $CARI_SELL$ is defined in a similar way, but it is based on sell trades. $CARI$ is the fund-level EAR and defined as the value-weighted average of the most recent EAR of all stocks held by the fund at the start of the quarter. SUR and $Dnews1$ are defined as $CARI$. SUR is the fund-level earnings surprise and $Dnews1$ is the fund-level earnings announcement direction. $ALPHA1F$, $ALPHA3F$, and $ALPHA4F$ are conditional fund alphas based on the market model, Fama-French three-factor model and the Carhart four-factor model, respectively. CS , CT , and AS are characteristics-based fund performance measures developed by Daniel et al. (1997).

VARIABLE	MEAN	SD	MIN	P1	P50	P99	MAX	N
2,822 distinct funds								
RET _{t+1} (% per quarter)	1.94	10.32	-81.06	-28.61	2.84	25.12	112.77	82,014
TNA (Mil)	1283	10263	1	2	161	18467	1168419	82,014
EXP_RATIO	1.33	0.53	0.00	0.17	1.30	2.68	16.36	82,014
TURNOVER (%)	83.55	92.76	0.00	0.00	62.00	404.00	3058.00	82,014
AGE (years)	12.7	11.5	2.1	2.5	8.8	59.3	85.6	82,014
NUMSTOCK	99	137	20	21	64	649	2809	82,014
TOTAL_LOAD (%)	1.25	1.73	0.00	0.00	0.76	8.50	8.50	82,014
FLOW (%)	2.29	18.30	-90.00	-33.86	-0.67	79.86	200.00	82,014
CARI (%)	0.80	1.47	-12.47	-2.49	0.65	5.37	24.40	82,014
SUR	4.54	0.45	1.11	3.33	4.54	5.74	8.12	82,014
DNEWS1	0.55	0.11	0.00	0.24	0.55	0.80	0.99	82,014
CARI_BUY(%)	0.07	0.54	-7.91	-1.44	0.04	1.71	8.50	81,352
CARI_SELL (%)	-0.04	0.55	-32.47	-1.67	-0.03	1.55	15.57	81,333
ALPHA1F (% per quarter)	-0.17	4.66	-49.81	-13.12	-0.24	13.69	100.68	81,945
ALPHA3F (% per quarter)	-0.23	4.06	-53.13	-11.21	-0.30	11.95	122.47	81,945
ALPHA4F (% per quarter)	-0.29	3.94	-55.29	-11.27	-0.31	10.99	139.60	81,945
CS (% per quarter)	0.22	3.95	-65.35	-10.56	0.15	11.97	68.58	80,968
CT (% per quarter)	0.08	13.94	-82.61	-34.49	-0.97	33.17	86.39	78,906
AS (% per quarter)	2.06	9.62	-87.37	-25.83	2.96	21.86	45.08	78,906

Table 2: Fama-MacBeth regression of quarterly fund returns

This table contains the results of the Fama-MacBeth regression of quarterly fund returns on the measure and other fund characteristics. *CARI_BUY* is the measure of the investment skills or information superiority of mutual funds. *CARI_SELL* is defined in a similar way, but it is based on sell trades. *Alpha3f* is the conditional alpha from the Fama-French three-factor model estimated using the fund's previous 24-months return history. *Alpha4f* is the conditional alpha from the Carhart four-factor model estimated in a way similar to *Alpha3f*. *CARI* is the fund-level EAR, defined as the value-weighted average EAR of all stocks held by a fund. *SUR* and *Dnews1* are defined as *CARI*. *SUR* is the fund-level earnings surprise and *Dnews1* is the fund-level earnings announcement direction. The *t* values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Regress on *CARI_BUY*

VARIABLES	(1) Alpha3f	(2) Alpha3f	(3) Alpha3f	(4) Alpha3f	(5) Alpha4f	(6) Alpha4f	(7) Alpha4f	(8) Alpha4f
CARI_BUY	0.188** (2.48)	0.124* (1.95)	0.203*** (2.65)	0.195** (2.58)	0.166** (2.32)	0.152** (2.37)	0.172** (2.35)	0.168** (2.35)
TNA	-0.009 (-0.64)	-0.010 (-0.65)	-0.011 (-0.78)	-0.011 (-0.75)	-0.024* (-1.73)	-0.023* (-1.69)	-0.025* (-1.81)	-0.025* (-1.80)
EXP_RATIO	-0.250*** (-4.08)	-0.256*** (-4.52)	-0.238*** (-3.87)	-0.239*** (-3.87)	-0.279*** (-5.00)	-0.267*** (-5.06)	-0.269*** (-4.70)	-0.274*** (-4.85)
TURNOVER	0.001 (1.30)	0.001 (1.22)	0.001 (1.39)	0.001 (1.31)	-0.000 (-0.22)	-0.000 (-0.21)	-0.000 (-0.20)	-0.000 (-0.30)
LAGE	-0.020 (-0.64)	-0.020 (-0.64)	-0.017 (-0.55)	-0.022 (-0.74)	-0.022 (-0.84)	-0.020 (-0.78)	-0.015 (-0.57)	-0.020 (-0.77)
TOTAL_LOAD	-0.007 (-0.38)	-0.004 (-0.23)	-0.011 (-0.59)	-0.011 (-0.58)	-0.005 (-0.25)	-0.005 (-0.27)	-0.005 (-0.29)	-0.005 (-0.29)
FLOW	0.553*** (2.84)	0.555*** (2.99)	0.574*** (3.02)	0.568*** (3.01)	0.434** (2.31)	0.466** (2.58)	0.481** (2.62)	0.466** (2.56)
CARI		0.091* (1.87)				0.025 (0.58)		
SUR			-0.124 (-1.07)				0.057 (0.58)	
DNEWS1				0.164 (0.32)				0.420 (1.04)
Constant	0.183 (1.01)	0.156 (0.84)	0.738 (1.33)	0.072 (0.22)	0.324** (2.00)	0.308* (1.88)	0.054 (0.12)	0.103 (0.38)
Observations	81,352	81,352	81,352	81,352	81,352	81,352	81,352	81,352
R^2	0.047	0.065	0.063	0.063	0.039	0.055	0.051	0.051
Number of groups	104	104	104	104	104	104	104	104

Panel B: Regress on *CAR1_SELL*

VARIABLES	(1) Alpha3f	(2) Alpha3f	(3) Alpha3f	(4) Alpha3f	(5) Alpha4f	(6) Alpha4f	(7) Alpha4f	(8) Alpha4f
CAR1_SELL	-0.095 (-1.52)	-0.071 (-1.16)	-0.101 (-1.62)	-0.094 (-1.51)	-0.083 (-1.35)	-0.081 (-1.36)	-0.089 (-1.44)	-0.086 (-1.39)
TNA	-0.009 (-0.64)	-0.010 (-0.67)	-0.011 (-0.78)	-0.011 (-0.75)	-0.025* (-1.82)	-0.024* (-1.78)	-0.026* (-1.90)	-0.026* (-1.89)
EXP_RATIO	-0.241*** (-3.88)	-0.247*** (-4.42)	-0.231*** (-3.74)	-0.231*** (-3.72)	-0.278*** (-5.04)	-0.265*** (-5.08)	-0.269*** (-4.78)	-0.273*** (-4.91)
TURNOVER	0.001 (1.36)	0.001 (1.21)	0.001 (1.43)	0.001 (1.36)	-0.000 (-0.18)	-0.000 (-0.21)	-0.000 (-0.16)	-0.000 (-0.26)
LAGE	-0.015 (-0.49)	-0.016 (-0.50)	-0.012 (-0.39)	-0.018 (-0.59)	-0.019 (-0.72)	-0.017 (-0.64)	-0.011 (-0.44)	-0.016 (-0.64)
TOTAL_LOAD	-0.010 (-0.55)	-0.005 (-0.29)	-0.013 (-0.72)	-0.013 (-0.70)	-0.004 (-0.23)	-0.003 (-0.19)	-0.004 (-0.25)	-0.004 (-0.25)
FLOW	0.554*** (2.77)	0.539*** (2.87)	0.575*** (2.94)	0.568*** (2.94)	0.425** (2.25)	0.445** (2.46)	0.472** (2.54)	0.455** (2.48)
CAR1		0.101** (2.02)				0.039 (0.88)		
SUR			-0.111 (-0.97)				0.068 (0.69)	
DNEWS1				0.207 (0.40)				0.461 (1.14)
Constant	0.163 (0.89)	0.131 (0.71)	0.664 (1.20)	0.031 (0.09)	0.316* (1.95)	0.293* (1.81)	-0.003 (-0.01)	0.074 (0.28)
Observations	81,333	81,333	81,333	81,333	81,333	81,333	81,333	81,333
R^2	0.045	0.065	0.062	0.062	0.038	0.054	0.049	0.049
Number of groups	104	104	104	104	104	104	104	104

Table 3: Return to quarterly fund portfolios sorted by the measure

This table presents quarterly returns for 10 equally weighted fund portfolios sorted by *CARI_BUY* from 1984 to 2009. *CARI_BUY* is the measure of the investment skills or information superiority of mutual funds. Fund portfolios are rebalanced quarterly. *Raw* is the raw stock return. *Alpha1f* is the conditional alpha from the market model, and it is estimated using a fund's previous 24-months return history. *Alpha3f* is the conditional alpha from the Fama-French three-factor model. *Alpha4f* is the conditional alpha from the Carhart four-factor model. *Raw*, *Alpha1f*, *Alpha3f* and *Alpha4f* are shown as percentage per quarter. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

	Raw	Alpha1f	Alpha3f	Alpha4f
1	1.67 (12.89)	-0.50 (-7.99)	-0.38 (-6.61)	-0.51 (-9.52)
2	1.84 (16.05)	-0.23 (-4.71)	-0.27 (-6.15)	-0.37 (-8.74)
3	1.85 (16.75)	-0.25 (-5.09)	-0.33 (-7.65)	-0.34 (-7.95)
4	1.84 (17.09)	-0.23 (-5.11)	-0.37 (-9.32)	-0.36 (-9.13)
5	1.90 (17.87)	-0.22 (-4.87)	-0.34 (-8.76)	-0.31 (-7.91)
6	1.94 (18.42)	-0.10 (-2.14)	-0.27 (-7.08)	-0.28 (-7.54)
7	2.07 (19.01)	-0.07 (-1.5)	-0.18 (-4.54)	-0.20 (-5)
8	2.01 (17.69)	-0.08 (-1.51)	-0.13 (-3.13)	-0.22 (-5.22)
9	2.12 (18.13)	-0.02 (-0.36)	-0.07 (-1.47)	-0.16 (-3.63)
10	2.14 (16.48)	0.02 (0.32)	0.10 (1.71)	-0.14 (-2.63)
2nd Half- 1st Half	0.23*** (3.22)	0.24*** (7.3)	0.23*** (7.94)	0.18*** (6.4)
5th Quintile - 1st Quintile	0.37*** (3.04)	0.36*** (6.35)	0.34*** (6.59)	0.29*** (5.92)
10th Decile - 1st Decile	0.47** (2.54)	0.52*** (5.79)	0.47*** (5.87)	0.37*** (4.79)

Table 4: Persistence of the measure: The measure level in the subsequent four quarters

This table shows the persistence of the measure by computing the measure level in the subsequent four quarters. *CARI_BUY* is the measure of the investment skills or information superiority of mutual funds. Note that *CARI_BUY* is scaled by 10^4 . The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

	Qtr + 1	Qtr +2	Qtr +3	Qtr +4
1	6.12 (10.12)	8.98 (14.76)	6.92 (11.78)	7.12 (12.25)
2	6.00 (11.9)	7.36 (14.57)	6.84 (13.38)	6.35 (12.52)
3	5.56 (12.03)	6.21 (13.62)	5.75 (12.56)	5.42 (11.42)
4	5.14 (12.06)	4.64 (10.88)	4.62 (10.58)	5.31 (12.07)
5	4.69 (11.35)	5.52 (12.95)	5.65 (13.09)	5.32 (12.24)
6	5.73 (13.23)	5.50 (12.47)	5.36 (12.12)	5.46 (12.23)
7	6.53 (14.87)	5.27 (11.71)	6.35 (13.82)	6.03 (13.07)
8	7.54 (15.09)	6.46 (13.22)	7.12 (14.45)	7.21 (14.38)
9	7.54 (14.39)	7.16 (13.4)	8.14 (15.27)	8.20 (15.64)
10	10.61 (16.67)	8.40 (13.66)	8.70 (14.22)	8.79 (14.76)
2nd Half- 1st Half	2.08*** (6.6)	0.02 (0.06)	1.18*** (3.72)	1.23*** (3.9)
5th Quintile - 1st Quintile	3.01*** (5.28)	-0.39 (-0.68)	1.54*** (2.75)	1.76*** (3.18)
10th Decile - 1st Decile	4.49*** (5.11)	-0.58 (-0.67)	1.78** (2.1)	1.67** (2.01)

Table 5: Persistence of the measure: Regression evidence

This table shows persistence of the measure by running the quarterly Fama-MacBeth regression of fund returns on past information about *CARI_BUY*. *CARI_BUY*(-*q*) is the *q*-quarter lagged *CARI_BUY*. *AVG_CARI_BUY* is the average value of *CARI_BUY* from Quarter -4 to Quarter -1. *AVGRANK_CARI_BUY* is the average decile rank of *CARI_BUY* from Quarter -4 to Quarter -1. *LALPHA3F* is one-quarter lagged *Alpha3f* and *LALPHA4F* is one-quarter lagged *Alpha4f*. The *t* values are in parentheses. *** indicates significance at 1%, ** at 5% and * at 10%, respectively.

Panel A: Past information about *CARI_BUY*

VARIABLES	(1) Alpha3f	(2) Alpha3f	(3) Alpha3f	(4) Alpha3f	(5) Alpha3f	(6) Alpha3f	(7) Alpha4f	(8) Alpha4f	(9) Alpha4f	(10) Alpha4f	(11) Alpha4f	(12) Alpha4f
CARI_BUY (-1)	0.164*** (2.98)						0.070 (1.34)					
CARI_BUY (-2)		0.073 (1.21)						0.015 (0.29)				
CARI_BUY (-3)			0.115 (1.63)						0.053 (0.81)			
CARI_BUY (-4)				0.101* (1.88)						0.095* (1.69)		
AVG_CARI_BUY					0.934*** (3.25)						0.463* (1.80)	
AVGRANK_CARI_BUY						0.053*** (3.28)						0.025* (1.85)
TNA	-0.006 (-0.44)	-0.007 (-0.53)	-0.006 (-0.44)	-0.004 (-0.29)	-0.007 (-0.56)	-0.008 (-0.58)	-0.018 (-1.38)	-0.020 (-1.52)	-0.020 (-1.47)	-0.019 (-1.45)	-0.020 (-1.51)	-0.020 (-1.48)
EXP_RATIO	-0.272*** (-4.57)	-0.286*** (-4.84)	-0.252*** (-4.21)	-0.269*** (-4.30)	-0.274*** (-4.60)	-0.277*** (-4.76)	-0.286*** (-5.50)	-0.300*** (-5.71)	-0.277*** (-5.18)	-0.286*** (-5.18)	-0.290*** (-5.27)	-0.287*** (-5.55)
TURNOVER	0.001 (0.94)	0.001 (1.03)	0.001 (1.18)	0.001 (1.21)	0.001 (1.04)	0.001 (0.96)	-0.000 (-0.26)	-0.000 (-0.12)	-0.000 (-0.02)	0.000 (0.02)	-0.000 (-0.01)	-0.000 (-0.21)
LAGE	-0.009 (-0.28)	-0.011 (-0.34)	-0.006 (-0.19)	-0.013 (-0.40)	-0.011 (-0.34)	-0.007 (-0.23)	-0.012 (-0.44)	-0.015 (-0.54)	-0.012 (-0.45)	-0.015 (-0.55)	-0.015 (-0.54)	-0.011 (-0.39)
TOTAL_LOAD	-0.005 (-0.25)	-0.003 (-0.16)	-0.007 (-0.39)	-0.006 (-0.33)	-0.009 (-0.46)	-0.005 (-0.27)	-0.005 (-0.26)	-0.003 (-0.14)	-0.005 (-0.29)	-0.005 (-0.28)	-0.008 (-0.39)	-0.005 (-0.29)
FLOW	0.555** (2.58)	0.606*** (3.01)	0.703*** (3.46)	0.624*** (3.17)	0.593** (2.50)	0.578*** (2.71)	0.429** (2.03)	0.479** (2.47)	0.576*** (2.93)	0.495** (2.61)	0.479** (2.08)	0.454** (2.18)
CARI	0.092* (1.79)	0.095* (1.86)	0.094* (1.84)	0.098* (1.91)	0.090* (1.76)	0.089* (1.73)	0.035 (0.78)	0.037 (0.82)	0.036 (0.80)	0.039 (0.86)	0.039 (0.87)	0.033 (0.74)
Constant	0.130 (0.67)	0.139 (0.73)	0.089 (0.46)	0.118 (0.61)	0.125 (0.66)	-0.083 (-0.37)	0.286* (1.69)	0.304* (1.80)	0.272 (1.61)	0.288* (1.68)	0.295* (1.73)	0.180 (0.98)
Observations	77,518	77,512	77,500	77,495	75,700	77,700	77,518	77,512	77,500	77,495	75,700	77,700
R ²	0.065	0.065	0.066	0.065	0.068	0.066	0.055	0.054	0.055	0.055	0.057	0.055
Number of groups	100	100	100	100	100	100	100	100	100	100	100	100

Panel B: Further controlling for lagged fund alpha

VARIABLES	(1) Alpha3f	(2) Alpha4f	(3) Alpha3f	(4) Alpha4f
AVG_CAR1_BUY	0.881*** (3.04)	0.475* (1.86)		
AVGRANK_CAR1_BUY			0.053*** (3.25)	0.026* (1.90)
TNA	-0.005 (-0.42)	-0.020 (-1.57)	-0.007 (-0.50)	-0.019 (-1.52)
EXP_RATIO	-0.250*** (-4.37)	-0.273*** (-5.00)	-0.250*** (-4.49)	-0.272*** (-5.28)
TURNOVER	0.001 (1.29)	0.000 (0.05)	0.001 (1.15)	-0.000 (-0.19)
LAGE	-0.023 (-0.77)	-0.017 (-0.62)	-0.018 (-0.62)	-0.014 (-0.52)
TOTAL_LOAD	-0.013 (-0.68)	-0.008 (-0.41)	-0.010 (-0.51)	-0.005 (-0.28)
FLOW	0.425* (1.93)	0.352 (1.56)	0.408** (2.08)	0.322 (1.58)
CAR1	0.069 (1.39)	0.020 (0.44)	0.069 (1.38)	0.014 (0.31)
LALPHA3F	0.065*** (3.27)		0.065*** (3.35)	
LALPHA4F		0.046** (2.59)		0.047*** (2.65)
Constant	0.138 (0.76)	0.309* (1.83)	-0.070 (-0.33)	0.193 (1.05)
Observations	75,700	75,700	77,700	77,700
R ²	0.106	0.088	0.102	0.085
Number of groups	100	100	100	100

Table 6: Decomposition of buys into first buys and non-first buys

In this table, buy trades are divided into first buys and non-first buys. Two new measures of the investment skills or information superiority of mutual funds are based on these two types of buys. *CAR1_FB* is defined on stocks that are first buys. *CAR1_nonFB* is defined on stocks that are buys but non-first buys. *AVGRANK_CAR1_FB* and *AVGRANK_CAR1_nonFB* are the average decile rank of *CAR1_FB* and *CAR1_nonFB* in the past 4 quarters, respectively. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

VARIABLES	(1) Alpha3f	(2) Alpha4f	(3) Alpha3f	(4) Alpha4f	(5) Alpha3f	(6) Alpha3f	(7) Alpha4f	(8) Alpha4f
CAR1_FB	0.199** (2.48)	0.206** (2.58)						
CAR1_nonFB			-0.027 (-0.24)	0.036 (0.33)				
AVGRANK_CAR1_FB					0.041*** (2.99)		0.021* (1.90)	
AVGRANK_CAR1_nonFB						0.035*** (2.80)		0.015 (1.19)
TNA	-0.006 (-0.46)	-0.018 (-1.36)	-0.008 (-0.57)	-0.021 (-1.59)	-0.006 (-0.45)	-0.007 (-0.51)	-0.019 (-1.40)	-0.019 (-1.45)
EXP_RATIO	-0.269*** (-4.43)	-0.288*** (-5.36)	-0.273*** (-4.57)	-0.288*** (-5.50)	-0.274*** (-4.63)	-0.274*** (-4.58)	-0.290*** (-5.47)	-0.289*** (-5.48)
TURNOVER	0.001 (1.12)	-0.000 (-0.15)	0.001 (1.07)	-0.000 (-0.10)	0.001 (0.91)	0.001 (0.95)	-0.000 (-0.29)	-0.000 (-0.31)
LAGE	-0.016 (-0.50)	-0.020 (-0.72)	-0.009 (-0.27)	-0.011 (-0.42)	-0.009 (-0.29)	-0.009 (-0.27)	-0.010 (-0.39)	-0.010 (-0.38)
TOTAL_LOAD	-0.006 (-0.29)	-0.004 (-0.20)	-0.003 (-0.19)	-0.002 (-0.13)	-0.005 (-0.26)	-0.006 (-0.30)	-0.004 (-0.19)	-0.004 (-0.22)
FLOW	0.592*** (3.02)	0.472** (2.49)	0.636*** (3.25)	0.509*** (2.68)	0.603*** (2.84)	0.585*** (2.73)	0.473** (2.27)	0.455** (2.17)
CAR1	0.091* (1.75)	0.031 (0.69)	0.098* (1.92)	0.034 (0.75)	0.096* (1.86)	0.096* (1.85)	0.038 (0.84)	0.037 (0.81)
Constant	0.147 (0.75)	0.304* (1.77)	0.145 (0.75)	0.304* (1.81)	-0.038 (-0.17)	-0.012 (-0.06)	0.195 (1.06)	0.227 (1.28)
Observations	76,005	76,005	77,910	77,910	77,511	77,511	77,511	77,511
R^2	0.066	0.056	0.065	0.055	0.064	0.065	0.054	0.055
Number of groups	100	100	100	100	100	100	100	100

Table 7: Characteristics-based measure of fund return

This table contains the return predictability of the measure using the characteristics-based fund performance measure developed by Daniel et al. (1997). In each quarter, we sort the funds into 10 portfolios using *CARI_BUY*. The funds are equally held in the portfolios. *CS*, *CT*, and *AS* are defined using Daniel et al.'s (1997) definitions. In Panel B, *EAR+* and *EAR-* represent stocks having positive and negative *EAR* during the most recent quarter, respectively. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Decomposition of fund return into *CS*, *CT* and *AS*

	CS	CT	AS
1	-0.00 (-0.09)	-0.12 (-0.67)	2.16 (18.2)
2	0.11 (2.6)	0.07 (0.41)	2.08 (18.85)
3	0.19 (4.64)	0.09 (0.57)	2.06 (19)
4	0.14 (3.51)	0.10 (0.64)	1.99 (19.01)
5	0.18 (4.92)	0.16 (1.08)	1.99 (19.08)
6	0.27 (7.21)	0.05 (0.34)	2.05 (19.85)
7	0.32 (7.87)	0.11 (0.73)	2.07 (19.73)
8	0.26 (6.39)	0.08 (0.51)	2.06 (19.38)
9	0.34 (7.63)	0.17 (1.07)	2.03 (19.02)
10	0.41 (7.03)	0.12 (0.73)	2.14 (18.92)
2nd Half- 1st Half	0.20*** (7.08)	0.05 (0.47)	0.01 (0.2)
5th Quintile - 1st Quintile	0.32*** (6.4)	0.17 (1.04)	-0.03 (-0.29)
10th Decile - 1st Decile	0.41*** (5.21)	0.24 (0.99)	-0.02 (-0.12)

Panel B: Decomposition of *CS* into negative and positive EAR regions

	EAR+	EAR-
1	0.12 (3.56)	-0.12 (-3.36)
2	0.13 (4.67)	-0.00 (-0.08)
3	0.15 (5.96)	0.03 (1.28)
4	0.13 (5.27)	0.02 (0.75)
5	0.15 (6.21)	0.04 (1.88)
6	0.20 (8.04)	0.08 (3.43)
7	0.25 (9.1)	0.08 (3.28)
8	0.24 (8.42)	0.03 (1.24)
9	0.26 (8.57)	0.08 (3.21)
10	0.31 (7.74)	0.09 (2.84)
2nd Half- 1st Half	0.12*** (6.3)	0.08*** (4.56)
5th Quintile - 1st Quintile	0.16*** (4.96)	0.15*** (4.86)
10th Decile - 1st Decile	0.19*** (3.68)	0.21*** (4.4)

Panel C: Fama-MacBeth regression

VARIABLES	(1) CS	(2) CS	(3) CS	(4) CS
CAR1_BUY	0.202** (2.35)	0.145** (2.11)	0.215** (2.55)	0.205** (2.41)
TNA	-0.025 (-1.35)	-0.025 (-1.44)	-0.025 (-1.41)	-0.019 (-0.90)
EXP_RATIO	-0.024 (-0.29)	-0.010 (-0.14)	-0.004 (-0.05)	0.030 (0.27)
TURNOVER	0.000 (0.53)	0.000 (0.30)	0.000 (0.48)	0.000 (0.41)
LAGE	0.018 (0.62)	0.017 (0.58)	0.022 (0.80)	0.019 (0.68)
TOTAL_LOAD	0.009 (0.52)	0.001 (0.04)	0.003 (0.18)	0.011 (0.52)
FLOW	0.124 (0.63)	0.155 (0.82)	0.140 (0.75)	0.123 (0.65)
CAR1		0.059 (0.93)		
SUR			0.046 (0.32)	
DNEWS1				0.672 (1.16)
Constant	0.337* (1.83)	0.340* (1.80)	0.143 (0.21)	-0.100 (-0.26)
Observations	80,391	80,391	80,391	80,391
R^2	0.049	0.074	0.072	0.071
Number of groups	104	104	104	104

Table 8: Return predictability when an earnings drift factor is introduced

This table shows the return predictability of *CAR1_BUY* for our sample funds from 1984 to 2009 when an earnings drift factor is used when calculating the abnormal fund return, *Alpha5f*. We run the quarterly Fama-MacBeth regression as in Table 2. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

VARIABLES	(1) Alpha5f	(2) Alpha5f	(3) Alpha5f	(4) Alpha5f
CAR1_BUY	0.179** (2.38)	0.186*** (2.70)	0.186** (2.41)	0.182** (2.40)
TNA	-0.028* (-1.91)	-0.028* (-1.87)	-0.028* (-1.95)	-0.029* (-1.94)
EXP_RATIO	-0.276*** (-4.47)	-0.269*** (-4.66)	-0.266*** (-4.25)	-0.268*** (-4.35)
TURNOVER	-0.000 (-0.34)	-0.000 (-0.24)	-0.000 (-0.27)	-0.000 (-0.33)
LAGE	-0.027 (-1.00)	-0.025 (-0.92)	-0.020 (-0.74)	-0.025 (-0.92)
TOTAL_LOAD	-0.010 (-0.52)	-0.008 (-0.43)	-0.010 (-0.57)	-0.010 (-0.56)
FLOW	0.380* (1.81)	0.420** (2.07)	0.430** (2.06)	0.414** (2.03)
CAR1		-0.003 (-0.07)		
SUR			0.022 (0.21)	
DNEWS1				0.108 (0.27)
Constant	0.310* (1.71)	0.297 (1.60)	0.196 (0.42)	0.245 (0.85)
Observations	81,352	81,352	81,352	81,352
R^2	0.041	0.055	0.052	0.052
Number of groups	104	104	104	104

Table 9: The effect of mutual fund style on the return predictability of the measure

In this table, we show the differential return predictability of the measure for growth and value funds. In Panel A, the sample funds are classified into growth and value funds according to investment codes. In Panel B, the sample fund quarters are classified into growth and value fund quarters using the fund-level log BM ratio. The t values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: The funds are classified by investment codes

VARIABLES	(1)	Growth funds (2)	(3)	(4)	Value funds (5)	(6)
	Alpha3f	Alpha4f	Alpha4f	Alpha3f	Alpha4f	Alpha4f
CAR1_BUY	0.045 (0.52)	0.043 (0.55)	0.048 (0.63)	0.345*** (3.36)	0.290*** (3.00)	0.261*** (2.80)
TNA	0.010 (0.51)	-0.002 (-0.09)	-0.002 (-0.11)	-0.023 (-1.28)	-0.035** (-2.27)	-0.034** (-2.21)
EXP_RATIO	-0.249*** (-3.31)	-0.220*** (-2.88)	-0.219*** (-2.94)	-0.228*** (-2.95)	-0.303*** (-4.36)	-0.290*** (-4.50)
TURNOVER	-0.000 (-0.07)	-0.001** (-2.09)	-0.001* (-1.88)	0.002** (1.99)	0.001 (0.95)	0.000 (0.85)
LAGE	0.008 (0.16)	-0.012 (-0.28)	-0.014 (-0.32)	-0.024 (-0.69)	-0.022 (-0.66)	-0.017 (-0.52)
TOTAL_LOAD	0.014 (0.68)	0.003 (0.13)	0.002 (0.11)	-0.021 (-0.88)	-0.006 (-0.24)	-0.005 (-0.21)
FLOW	0.528* (1.98)	0.339 (1.32)	0.384 (1.53)	0.645*** (2.90)	0.522** (2.59)	0.539*** (2.71)
CAR1			0.006 (0.12)			0.031 (0.72)
Constant	0.141 (0.63)	0.230 (1.08)	0.241 (1.14)	0.156 (0.75)	0.345* (1.87)	0.316* (1.71)
Observations	33,850	33,850	33,850	47,502	47,502	47,502
R^2	0.064	0.058	0.075	0.069	0.058	0.075
Number of groups	104	104	104	104	104	104

Panel B: The funds are classified by the fund-level log BM ratio

VARIABLES	(1)	Growth funds (2)	(3)	(4)	Value funds (5)	(6)
	Alpha3f	Alpha4f	Alpha4f	Alpha3f	Alpha4f	Alpha4f
CAR1_BUY	0.168** (2.01)	0.112 (1.32)	0.102 (1.25)	0.177* (1.78)	0.170* (1.92)	0.167* (1.97)
TNA	-0.002 (-0.14)	-0.004 (-0.22)	-0.004 (-0.22)	-0.012 (-0.62)	-0.036** (-2.08)	-0.036** (-2.08)
EXP_RATIO	-0.180** (-2.37)	-0.207*** (-2.79)	-0.205*** (-2.78)	-0.303*** (-3.93)	-0.345*** (-4.92)	-0.320*** (-4.81)
TURNOVER	0.000 (0.66)	-0.001 (-1.53)	-0.001 (-1.34)	0.001 (1.61)	0.000 (0.72)	0.000 (0.55)
LAGE	0.019 (0.54)	0.007 (0.21)	-0.001 (-0.03)	-0.068 (-1.55)	-0.058 (-1.48)	-0.051 (-1.29)
TOTAL_LOAD	-0.038* (-1.72)	-0.025 (-1.09)	-0.021 (-0.89)	0.013 (0.55)	0.015 (0.63)	0.012 (0.50)
FLOW	0.596** (2.19)	0.483* (1.86)	0.491* (1.93)	0.749*** (3.23)	0.573** (2.47)	0.629*** (2.77)
CAR1			-0.014 (-0.30)			0.033 (0.62)
Constant	-0.115 (-0.51)	0.107 (0.54)	0.122 (0.62)	0.474** (2.54)	0.518*** (2.77)	0.498*** (2.66)
Observations	40,586	40,586	40,586	40,686	40,686	40,686
R ²	0.065	0.057	0.074	0.066	0.059	0.081
Number of groups	104	104	104	104	104	104

Table 10: Sub-period analysis

In this table, the sample period is divided into three sub-periods: (1) 1984 to 1992, (2) 1993 to 2000, and (3) 2001 to 2009. Note the last sub-period starts with the introduction of Regulation FD. *CAR1_BUY* is the measure of the investment skills or information superiority of mutual funds. *Alpha3f* is the conditional alpha from the Fama-French three-factor model estimated using a fund's previous 24-months return history. *Alpha4f* is the conditional alpha from the Carhart four-factor model estimated in a way similar to *Alpha3f*. *CAR1* is the fund-level EAR, and it is defined as the value-weighted average EAR of all stocks held by a fund. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5%, and * at 10%, respectively.

VARIABLES	1984:1992		1993:2000		2001:2009	
	(1) Alpha3f	(2) Alpha4f	(3) Alpha3f	(4) Alpha4f	(5) Alpha3f	(6) Alpha4f
CAR1_BUY	-0.001 (-0.00)	0.067 (0.44)	0.142* (1.73)	0.146* (1.89)	0.234** (2.50)	0.244*** (2.95)
TNA	-0.016 (-0.56)	-0.033 (-1.12)	0.016 (0.49)	-0.025 (-1.08)	-0.027* (-1.76)	-0.012 (-0.67)
EXP_RATIO	-0.183* (-1.86)	-0.239*** (-3.20)	-0.241** (-2.55)	-0.297*** (-3.42)	-0.343*** (-3.39)	-0.268** (-2.44)
TURNOVER	0.001 (1.31)	-0.000 (-0.32)	0.003** (2.16)	0.001 (0.92)	-0.002* (-1.71)	-0.001* (-1.90)
LAGE	-0.085 (-1.35)	-0.106* (-1.95)	-0.064 (-1.66)	-0.027 (-0.82)	0.083 (1.58)	0.071* (1.80)
TOTAL_LOAD	0.001 (0.09)	-0.002 (-0.17)	-0.049 (-1.45)	-0.023 (-0.68)	0.030 (0.70)	0.008 (0.20)
FLOW	0.537 (1.29)	0.388 (0.90)	0.779*** (3.07)	0.741*** (2.77)	0.376 (1.46)	0.300 (1.63)
CAR1	0.121 (1.49)	0.100 (1.22)	0.131 (1.29)	-0.017 (-0.21)	0.024 (0.34)	-0.013 (-0.21)
Constant	0.456 (1.60)	0.687*** (3.00)	-0.148 (-0.36)	0.282 (0.80)	0.127 (0.46)	-0.048 (-0.18)
Observations	11,736	11,736	22,830	22,830	46,786	46,786
R^2	0.058	0.055	0.079	0.061	0.059	0.048
Number of groups	36	36	32	32	36	36

Table 11: Stock performance evidence

This table contains stock-performance evidence for the fund return predictability of the measure *CARI_BUY*. The analysis involves all stocks held by the sample funds from 1984 to 2009. A stock can be held by multiple mutual funds. Therefore, in Panel A, the mean of *CARI_BUY* for all the mutual funds currently holding this stock is considered as the stock under-value score. The score measures investors' sophistication or level of information. At the start of each quarter, we sort stocks into quintiles by this score. We also independently sort stocks into three groups by their most recent EAR. One-quarter ahead abnormal stock returns are collected for the 15 equally weighted stock portfolios and tabulated in the table. In Panel B, the mean of *AVGRANK_CARI_BUY* for all the mutual funds holding the stock is used as the stock under-value score. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: The stock under-value score is based on the fund measure *CARI_BUY*

Stock under-value score quintile rank	EAR tercile rank		
	1	2	3
1	-0.73 (-3.57)	0.11 (0.77)	0.98 (5.68)
2	-1.16 (-5.79)	0.21 (1.09)	1.28 (6.64)
3	-0.93 (-4.46)	0.21 (1.17)	1.35 (7.5)
4	-0.97 (-5.12)	0.29 (1.76)	1.31 (8.12)
5	-1.03 (-5.03)	0.45 (3.7)	1.21 (7.43)
5th Quintile - 1st Quintile	-0.31 (-1.06)	0.34* (1.8)	0.24 (1)

Panel B: The stock under-value score is based on the fund measure *AVGRANK_CARI_BUY*

Stock under-value score quintile rank	EAR tercile rank		
	1	2	3
1	-1.30 (-5.61)	-0.12 (-0.57)	1.59 (8.21)
2	-1.12 (-6)	0.32 (1.78)	1.22 (7.51)
3	-0.89 (-4.33)	0.15 (1.09)	1.35 (7.92)
4	-0.86 (-4.52)	0.31 (2.19)	1.02 (6.43)
5	-0.73 (-3.7)	0.45 (4.07)	1.09 (6.46)
5th Quintile - 1st Quintile	0.57* (1.87)	0.56** (2.43)	-0.51** (-1.98)

Table 12: Unconditional alphas from monthly portfolios

In each month from 1984 to 2009, we sort the sample funds into 10 portfolios using the measure *CARI_BUY*. The funds are equally weighted in the portfolios. The time series of the returns for each portfolio are then projected to risk factors. The resulting alphas are tabulated in this table. *RAW* is the raw stock return. *CAPM* is the alpha from the market model. *FF3* is the alpha from the Fama-French three-factor model. *CARHART4* is the alpha from the Carhart four-factor model. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

	RAW	CAPM	FF3	CARHART4
1	0.74 (2.45)	-0.20 (-2.83)	-0.18 (-3.24)	-0.16 (-2.71)
2	0.80 (2.89)	-0.10 (-2.34)	-0.11 (-3.13)	-0.10 (-2.4)
3	0.81 (3.07)	-0.07 (-1.73)	-0.09 (-2.61)	-0.07 (-1.87)
4	0.83 (3.2)	-0.05 (-1.05)	-0.09 (-2.99)	-0.06 (-1.88)
5	0.83 (3.28)	-0.04 (-0.69)	-0.07 (-2.09)	-0.06 (-1.87)
6	0.88 (3.48)	0.01 (0.11)	-0.03 (-0.73)	-0.03 (-0.59)
7	0.87 (3.39)	-0.01 (-0.19)	-0.03 (-0.91)	-0.05 (-1.31)
8	0.87 (3.35)	-0.03 (-0.45)	-0.04 (-0.99)	-0.06 (-1.4)
9	0.89 (3.33)	-0.02 (-0.25)	-0.00 (-0.06)	-0.04 (-0.74)
10	0.91 (3.02)	-0.05 (-0.43)	0.03 (0.36)	-0.05 (-0.72)
2nd Half - 1st Half	0.08** (2.1)	0.07* (1.78)	0.09** (2.48)	0.05 (1.43)
5th Quintile - 1st Quintile	0.13** (2.13)	0.12* (1.89)	0.16** (2.54)	0.09 (1.57)
10th Decile - 1st Decile	0.17** (2.27)	0.15** (2.06)	0.20*** (2.68)	0.11* (1.78)

Table 13: Simulated mutual funds

We simulate 1,200 mutual funds every month from 1984 to 2009. These hypothetical stock portfolios are rebalanced each month, and 10% of stocks are renewed. In Column 1, stocks are randomly chosen with equal probability. In Column 2, stocks are randomly chosen with probability proportional to firm size. The monthly fund return is the value-weighted return for all the stocks held at the start of the month. The measure *CARI_BUY* is obtained for each simulated fund quarter. At the start of each quarter, we sort the funds into 10 portfolios using *CARI_BUY* and collect the equally weighted fund return for each portfolio during this quarter. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

	(1)	(2)
Rank	Equal Probability	Proportional to Size Probability
1	0.05 (1.44)	-0.11 (-8.43)
2	0.11 (2.96)	-0.09 (-7.25)
3	0.05 (1.5)	-0.11 (-8.42)
4	0.13 (3.65)	-0.10 (-7.62)
5	0.09 (2.67)	-0.10 (-7.86)
6	0.07 (1.98)	-0.11 (-8.63)
7	0.08 (2.35)	-0.12 (-9.08)
8	0.03 (0.89)	-0.11 (-8.32)
9	0.08 (2.37)	-0.08 (-6.36)
10	0.12 (3.44)	-0.11 (-8.58)
2nd Half - 1st Half	-0.01 (-0.44)	-0.00 (-0.39)
5th Quintile - 1st Quintile	0.02 (0.6)	0.01 (0.46)
10th Decile - 1st Decile	0.07 (1.31)	-0.00 (0.00)

Table 14: Comparison with other measures of fund skills

This table reports regressions of quarterly fund returns measured by *Alpha4f* on various measures of fund skills. *CAR1_BUY* is the measure of the investment skills or information superiority of mutual funds. *WEAR* is a fund skill measure in Wermers et al. (2010) motivated by Baker et al. (2009). *SIM* is a fund skill measure in Wermers et al. (2010) motivated by Cohen, Coval, and Pastor (2005), capturing the idea that stocks are of high quality as other skillful funds also own them. *RETGAP* is the return gap measure from Kacperczyk, Sialm, and Zheng (2006). *ICI* is the industry concentration index of Kacperczyk, Sialm, and Zheng (2005). *ACTIVESHARE* is the measure of deviation of fund holding from the benchmark index in Cremers and Petajisto (2009). Control variables are the same as in Column 5 of Table 2. The *t* values are provided in the parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Intercept	CAR1_BUY	WEAR	SIM	RETGAP	ICI	ACTIVESHARE	Control variables	NOBS	Start	End	R ²
0.308** (2.17)	0.156** (2.22)						Yes	81,898	19841	20094	3.89%
0.321** (2.26)		0.724 (0.79)					Yes	81,857	19841	20094	3.55%
0.298** (2.19)			0.238 (1.63)				Yes	81,918	19841	20094	5.82%
0.561*** (2.89)				0.174** (2.33)			Yes	48,271	19841	20071	6.85%
0.296* (1.83)							Yes	58,955	19841	20072	5.10%
0.266* (1.81)					0.750** (2)		Yes	81,918	19841	20094	4.58%
-0.115 (-0.34)						0.560 (1.54)	Yes	44,720	19901	20064	5.62%
0.307** (2.15)	0.188** (2.06)	-1.372 (-1.07)					Yes	81,857	19841	20094	4.23%
0.290** (2.14)	0.137* (1.98)		0.227 (1.55)				Yes	81,898	19841	20094	6.41%
0.539*** (2.79)	0.113 (1.35)			0.169** (2.28)			Yes	48,264	19841	20071	7.60%
0.270* (1.68)	0.202** (2.36)						Yes	58,940	19841	20072	5.87%
0.248* (1.69)	0.158** (2.31)				0.775** (2.11)		Yes	81,898	19841	20094	5.19%
-0.139 (-0.42)	0.136* (1.8)					0.568 (1.58)	Yes	44,713	19901	20064	6.28%
-0.049 (-0.14)	0.167* (1.9)	-1.578 (-0.8)	0.403** (2.12)	0.128* (1.69)	0.464 (0.43)	0.512 (1.37)	Yes	40,515	19901	20064	12.89%

Figure 2: Persistence of the measure: Average decile ranks of *CARI_BUY* in the surrounding 8 quarters

In each quarter, we sort the funds into deciles using *CARI_BUY*. The average decile ranks of *CARI_BUY* for the 10 fund portfolios in the 8 quarters before and after the portfolio formation are plotted in the following figure. Note the rank value of Quarter 0 is the original decile rank divided by 10 plus five.⁷⁴

⁷⁴ Therefore, the ranks are transformed from 1, 2...10 to 5.1, 5.2...5.9.

Appendix A: Monthly stock portfolios sorted by *EAR*

This table shows the post-earnings drift for all U.S. stocks in the CRSP and COMPUSTAT database from 1980 to 2009. In each quarter, 10 stock portfolios are formed based on a stock's 3-day *EAR*. The portfolios are held for 3 months before rebalancing in the next quarter. Note that each stock is equally held in the portfolios. We collect the monthly returns for such portfolios and also project them to the whole time series for factor returns. *RAW* is the raw stock return. *CAPM* is the alpha from the market model. *FF3* is the alpha from the Fama-French three-factor model. *CARHART4* is the alpha from the Carhart four-factor model. The *t* values are in parentheses. *** indicates the significance level at 1%, ** at 5% and * at 10%, respectively.

Panel A: Equally weighted portfolios

	RAW	CAPM	FF3	CARHART4
1	0.99 (2.13)	-0.24 (-0.78)	0.16 (0.69)	-0.28 (-1.34)
2	1.06 (2.83)	-0.07 (-0.35)	0.09 (0.67)	-0.15 (-1.35)
3	1.23 (3.69)	0.13 (0.74)	0.22 (2)	0.03 (0.29)
4	1.27 (4)	0.19 (1.13)	0.26 (2.42)	0.07 (0.73)
5	1.36 (4.4)	0.30 (1.85)	0.31 (3.36)	0.17 (2.02)
6	1.31 (4.28)	0.26 (1.55)	0.26 (2.77)	0.13 (1.5)
7	1.36 (4.37)	0.28 (1.71)	0.26 (2.93)	0.15 (1.72)
8	1.47 (4.63)	0.37 (2.16)	0.37 (3.46)	0.27 (2.71)
9	1.54 (4.3)	0.38 (1.9)	0.45 (3.71)	0.30 (2.73)
10	1.88 (4.2)	0.58 (2.09)	0.76 (4.52)	0.54 (3.44)
2nd Half - 1st Half	0.32*** (6.38)	0.31*** (5.9)	0.21*** (3.49)	0.31*** (5.82)
5th Quintile - 1st Quintile	0.68*** (7.94)	0.64*** (6.95)	0.48*** (4.87)	0.63*** (7.03)
10th Decile - 1st Decile	0.88*** (7.31)	0.82*** (6.07)	0.60*** (3.93)	0.81*** (5.9)

Panel B: Value-weighted portfolios

	RAW	CAPM	FF3	CARHART4
1	0.95 (2.35)	-0.21 (-1.12)	0.18 (1.03)	-0.22 (-1.18)
2	1.14 (3.81)	0.17 (1.24)	0.31 (2.32)	0.11 (0.85)
3	1.15 (4.51)	0.15 (1.29)	0.25 (2.27)	0.09 (0.86)
4	1.03 (3.89)	0.03 (0.32)	0.10 (1.07)	-0.01 (-0.09)
5	1.18 (4.64)	0.18 (1.89)	0.24 (2.18)	0.14 (1.32)
6	0.99 (3.97)	0.01 (0.15)	0.10 (1.18)	0.03 (0.37)
7	1.05 (4.12)	0.06 (0.7)	0.05 (0.61)	0.01 (0.12)
8	1.07 (3.97)	0.08 (0.91)	0.07 (0.72)	0.05 (0.55)
9	1.10 (3.89)	0.05 (0.45)	0.12 (1.01)	0.04 (0.36)
10	0.80 (2.02)	-0.47 (-2.57)	-0.23 (-1.1)	-0.39 (-2.09)
2nd Half - 1st Half	-0.09 (-1.32)	-0.11 (-1.37)	-0.19*** (-2.6)	-0.08 (-1.01)
5th Quintile - 1st Quintile	-0.13 (-0.96)	-0.21 (-1.36)	-0.32** (-2.24)	-0.16 (-1.04)
10th Decile - 1st Decile	-0.15 (-0.73)	-0.26 (-1.17)	-0.40* (-1.84)	-0.16 (-0.76)