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Security Analysts and Capital Market Anomalies☆

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Abstract

We examine the value and efficiency of analyst recommendations through the lens of capital market anomalies. We find that analysts do not fully use the information in anomaly signals when making recommendations. Specifically, analysts tend to give more favorable consensus recommendations to stocks classified as overvalued, and, more importantly, these stocks subsequently tend to have particularly negative abnormal returns. Analysts whose recommendations are better aligned with anomaly signals are more skilled and elicit stronger recommendation announcement returns. Our findings suggest that analysts' biased recommendations could be a source of market friction that impedes the efficient correction of mispricing.

JEL classification: G12, G14

Keywords: Analysts; Analyst recommendations; Anomalies; Mispricing; Market efficiency

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"Wall Street analysts know their companies. You should cut a research report in two. The first part, the information about the company and its prospects, is probably pretty good. The second part, the recommendation, should be used as kindling. We use analyst information, but we don't use the recommendations very often." *-David Dreman*

1. Introduction

A longstanding debate in the finance and accounting literature concerns whether security analysts' research helps to improve stock market efficiency. Early studies that examine market reactions to analyst earnings forecast revisions or recommendation changes tend to support the notion that analysts are skilled information processors (Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001). That is, analysts' information-production role helps to improve price efficiency. However, recent studies question the usefulness of analyst research outputs, arguing that analysts' incentives to gain investment banking business, generate trading commissions, and curry favor with management for access to private information can compromise their integrity and objectivity.[1] More generally, Bradshaw, Richardson, and Sloan (2006) find that a firm's level of external financing is a more important driver of analyst optimism than existing investment banking ties. This suggests that even unaffiliated analysts could upwardly bias their forecasts or recommendations in anticipation of future business.

In addition to conflicts of interest arising from investment banking/brokerage affiliations, analysts' recommendations or forecasts may be inefficient due to behavioral biases (La Porta, 1996). Several recent studies explicitly model analysts' biased expectations and examine their effect on stock mispricing. Cen, Hillary, and Wei (2013) show that analysts anchor their earnings forecasts too close to the industry medians. Bouchaud, Krueger, Landier, and Thesmar (2018) find

[1] See, for instance, Lin and McNichols (1998), Chen and Matsumoto (2006), and Cowen, Groysberg, and Healy (2006).

that analysts' expectations are sticky in the short run and that they underreact to persistence in firms' profitability. Bordalo, Gennaioli, La Porta, and Shleifer (2018) find that analysts are extrapolative in their long-term growth forecasts and overreact to past earnings growth.

In this paper, we address this important question by examining whether analysts exploit well-documented stock return anomalies when making recommendations. Over the last several decades, researchers have discovered numerous cross-sectional stock return anomalies. Irrespective of the sources of return predictability, these anomalies represent publicly available information, of which skilled agents, such as analysts, should be able to take advantage. If analysts are truly sophisticated, informed, and unbiased, they should exploit such well-known sources of return predictability when making recommendations.[2]

We propose two competing views of analyst research that offer opposite predictions to our research question. The *sophisticated analyst hypothesis* predicts that analysts should on average tilt their recommendations to be consistent with anomaly prescriptions. In contrast, the *biased analyst hypothesis* suggests that analyst recommendations are unrelated or even contradictory to anomaly prescriptions. Most importantly, the two competing hypotheses have different asset pricing implications when analyst recommendations disagree with anomaly prescriptions. The sophisticated analyst hypothesis predicts that when analyst recommendations contradict anomaly prescriptions, anomaly stocks should not be associated with future abnormal returns. In sharp contrast, the biased analyst hypothesis predicts that anomaly returns can be amplified when analysts disagree with anomaly prescriptions, especially if certain groups of investors naïvely or

[2] We focus on analyst recommendations because they directly reflect analysts' view of the relative over- or under-valuation of a stock, while analysts' forecasts of firm earnings do not directly correspond to their perception of relative misevaluation.

strategically follow analyst recommendations.[3] In other words, biased analyst recommendations are a potential source of market friction that contributes to stock mispricing.

Following Stambaugh, Yu, and Yuan (2012), we construct 11 prominent asset pricing anomalies using a sample of available analyst recommendation data from the Institutional Brokers' Estimate System (I/B/E/S). We first show that during our sample period of 1993-2014, all long-short portfolios based on these 11 anomalies generate significant Fama and French (1993) three-factor alphas, ranging from 0.35% to 1.09% per month. Following Stambaugh and Yuan (2017), we also create two composite mispricing scores, MGMT and PERF, which generate monthly three-factor alphas of 0.86% and 0.99%, respectively.[4] This strong return predictability suggests that anomaly signals are part of the information set that analysts can use when making stock recommendations.

To examine whether analysts incorporate anomaly signals into their recommendation decisions, we analyze the level and change of analyst recommendations during the window of anomaly portfolio formation.[5] The results strongly reject the sophisticated analyst hypothesis. First, not only do analysts fail to tilt their recommendations to take advantage of anomalies, but also their recommendations are often contradictory to anomaly predictions. This tendency is

[3] Mikhail, Walther, and Willis (2007) and Malmendier and Shanthikumar (2007) find that small investors naïvely follow analyst recommendations without accounting for analysts' biased incentives. Brown, Wei, and Wermers (2013) show that mutual funds tend to herd into stocks with consensus sell-side analyst upgrades and herd out of stocks with consensus downgrades; they further show that herding by career-concerned fund managers is price destabilizing.

[4] MGMT mainly consists of anomalies related to managerial actions, and PERF mainly consists of anomalies related to firm performance.

[5] We measure the change in recommendations by taking the difference between the current consensus recommendation and its value one year ago.

particularly strong for anomalies related to equity issuance and investment. For example, for MGMT, the mean recommendation value is 4.07 for stocks in the short leg and 3.52 for stocks in the long leg with a difference of -0.55, which is highly significant. In contrast, analyst recommendations seem to be more consistent with prescriptions of the anomalies associated with firm performance (PERF), such as gross profitability and return on assets, although the relation is weak and not monotonic. The results are similar for recommendation changes, which is particularly puzzling. This finding suggests that analysts actively revise opinions on anomaly stocks, but their views tend to be in the wrong direction of anomaly predictions. Thus, neither analyst inattention nor stale recommendation stories can fully explain our findings.

The difference in analyst behavior across the two categories of anomalies is consistent with evidence in the literature that analysts tend to issue overly optimistic growth forecasts or recommendations for firms characterized by high growth, large capital spending, and equity financing needs. Such firms are more likely to be potential investment banking clients of the brokerage firms employing the analysts. Analysts are also likely to issue more favorable recommendations for better-performing firms with high profitability or past winners.

Most importantly, analyst recommendation behavior itself is not sufficient to distinguish the two competing hypotheses. Analysts may have superior (private) information such that even when their recommendations contradict anomaly prescriptions, the information value of their recommendations could offset that of the anomalies. We therefore examine anomaly returns when analyst recommendations confirm or contradict anomaly signals. The results reveal the same message. When analyst recommendations and anomaly prescriptions are contradictory, anomaly returns are amplified, especially for anomalies in the PERF category.

The abnormal returns in inconsistent cases are larger than those in consistent cases for all 11 anomalies, and significantly so for seven anomalies. For example, the long-short portfolio based on PERF generates a monthly three-factor alpha of 1.57% for the inconsistent case, whereas it is only 0.90% for the consistent case. The result is more pronounced in the short leg of anomalies with the most favorable recommendations, which earns a particularly large negative return. This is in line with the idea that short selling overvalued stocks is costlier than correcting underpriced stocks (Nagel, 2005; Stambaugh, Yu, and Yuan, 2015), especially when betting against analyst consensus. The amplification effect of biased analyst recommendations on anomalies is not driven by other firm characteristics. The results of the Fama and MacBeth (1973) regressions after controlling for standard return predictors are in line with portfolio sorting results.

The amplification effect of biased recommendations on anomaly returns suggests that some investors who follow analyst opinions or think like analysts might trade in the same direction of recommendations over the portfolio formation period. If this is the case, investors' excess demand will lead to further mispricing. Anomaly returns are thus amplified as prices subsequently revert to fundamental values. Using changes in stock ownership by mutual funds as a proxy for investors' demand, we find evidence supporting this underlying channel. For both the long and short legs of anomaly portfolios, stocks with favorable consensus recommendations experience significantly larger mutual fund net buys over the portfolio formation window compared with stocks with unfavorable recommendations. Moreover, the effect of favorable recommendations on mutual fund demand is more pronounced for stocks in the short leg of the anomalies, consistent with our portfolio return patterns.

The above findings could mask significant heterogeneity across individual analysts who differ in their skill in generating and/or incentives to generate informative recommendations. To shed light on this issue, for each analyst at the end of each year, we calculate the correlation between stocks' anomaly rankings and recommendation values, using all recommendations issued by the analyst over the past three years. Consistent with the idea that this correlation metric captures an analyst's skill or unbiasedness, we find that analysts with a higher correlation metric elicit stronger market reactions when announcing recommendation changes. We further explore the market efficiency implications of skilled analysts and find that stocks followed by a larger fraction of skilled analysts have significantly attenuated anomaly returns.

We consider several potential explanations for analysts' tendency to recommend contrary to anomaly prescriptions.[6] First, analysts may simply be unaware of the return predictability of these anomalies before their discovery by academics (McLean and Pontiff, 2016). However, we find that analysts' tendency to recommend overvalued stocks more favorably is still significant for six anomalies in the post-publication period, suggesting that analysts' unawareness of expected return information in the anomalies is unlikely to fully explain our findings. Second, analysts may be reluctant to incorporate anomaly signals into their recommendations because their institutional clients can face severe constraints when trading these stocks. Using firm size and bid-ask spread as proxies for trading frictions, we find very similar results for big or highly liquid stocks,

[6] One possibility not explored here is that analysts may incorporate many potential anomaly variables into their recommendations. However, precisely because many investors follow their recommendations, these anomalies disappear and thus cannot be detected by researchers. Thus, by definition, only those anomalies with inconsistent recommendations survive. However, anomaly returns are still significant when recommendations are consistent with anomaly predictions, suggesting that investors may not fully follow analyst recommendations and that anomalies are unlikely to be completely corrected by consistent recommendations. This argument also suggests that biased analyst recommendation alone cannot fully explain the existence of anomalies. We thank the referee for suggesting this argument.

suggesting that limits-to-arbitrage concerns on the part of analysts are unlikely to explain our findings. Finally, analyst recommendations can be strategically biased to cater to institutional investors' preferences for overvalued stocks (Edelen, Ince, and Kadlec, 2016). However, we find very similar results for stocks partitioned by institutional ownership, suggesting that the catering incentive cannot fully explain our findings.

Analyst recommendations can be biased due to misaligned incentives or behavioral bias. Based on the Baker-Wurgler (2006) sentiment index, we find that analyst recommendations are more biased toward overvalued stocks and that the amplification effect of biased recommendations on anomaly returns is more pronounced during the high-sentiment period than during the low-sentiment period. This evidence suggests that the behavioral bias of analysts may partially explain their overly optimistic (pessimistic) recommendations for overvalued (undervalued) stocks.

Using analyst data from Zacks Investment Research over an earlier sample period, Barber et al. (2001) and Jegadeesh, Kim, Krische, and Lee (2004) document the investment value of both the level and change of analyst consensus recommendations. To reconcile their evidence with our finding that analyst consensus recommendations are on average inefficient, we reexamine the unconditional return predictability of analyst consensus recommendations. Using I/B/E/S data over the sample period from 1993 to 2014, we do not find any return predictability for the level of analyst consensus recommendations. While we do find some return predictability for the change of consensus recommendations over the full sample period, it is concentrated only in the 1993-2000 period. Overall, we conclude that the seeming contradiction between our results and those of prior studies is mainly attributable to the different sample periods studied.

In a recent concurrent working paper, Engelberg, McLean, and Pontiff (2018b) similarly show that analysts' price forecasts and recommendations often contradict anomaly predictions.

Our paper differs from theirs by further showing that anomaly returns are significantly amplified when analyst opinions contradict anomaly signals. We thus provide stronger evidence that analysts' biased recommendations can contribute to the persistence of anomalies. Moreover, we develop a simple method to identify skilled analysts ex ante.

2. Related literature

2.1. Cross-sectional asset-pricing anomalies

Many stock return anomalies have been discovered in recent decades. Although the sources of these anomalies' return predictability are still under debate, the large abnormal returns generated by some of them are well-established. In this subsection, we start with the 11 prominent anomalies extensively examined by Stambaugh et al. (2012) to shed light on the inference of analyst behavior and return anomalies.

Stambaugh and Yuan (2017) further propose two mispricing factors that are constructed from these 11 prominent anomalies. They begin by separating the 11 anomalies into two clusters based on the similarity in time-series anomaly returns and cross-sectional anomaly rankings. The first cluster consists of six anomalies: net stock issuance (NSI), composite equity issuance (CEI), accruals (Accrual), net operating assets (NOA), asset growth (AG), and investment to assets (IA). The authors find that these variables are most likely to be directly affected by the decisions of firm managers. Therefore, the average ranking score based on these six anomalies reflects the commonality of mispricing caused by firm managers' decisions. The authors denote the pricing factor arising from this first cluster as MGMT. The second cluster of anomalies includes gross profitability (GP), return on assets (ROA), momentum (MOM), financial distress (Distress), and O-score. These five anomaly variables are more related to firm performance and less directly controlled by firm management. Stambaugh and Yuan (2017) denote the pricing factor generated from this second cluster as PERF. We describe each anomaly in detail as follows:[7]

Cluster I anomalies (MGMT):

(1) Net stock issuance (NSI): Ritter (1991), Loughran and Ritter (1995), and Pontiff and Woodgate (2008) find that firms issuing new shares underperform the market in the following three to five years. Net stock issuance is calculated as the growth rate of the split-adjusted shares outstanding in the previous year.

(2) Composite net equity issuance (CEI): Daniel and Titman (2006) and Fama and French (2008) find that firms with higher composite net equity issues earn lower future risk-adjusted returns. The composite net equity issuance includes any actions that increase share issuance (such as seasoned equity offerings and share-based acquisitions) minus any actions that reduce share issuance (such as share repurchases) in the previous year.

(3) Accounting accruals (Accrual): Sloan (1996) shows that firms with high total accounting accruals subsequently earn lower risk-adjusted returns.

(4) Net operating assets (NOA): Hirshleifer, Hou, Teoh, and Zhang (2004) show that firms with higher net operating assets subsequently earn lower risk-adjusted returns.

(5) Asset growth (AG): Cooper, Gulen, and Schill (2008) and Titman, Wei, and Xie (2013) report that firms with higher growth in total assets subsequently earn lower risk-adjusted returns.

(6) Investment to assets (IA): Titman, Wei, and Xie (2004) and Xing (2008) find that firms with higher past investment earn lower future risk-adjusted returns.

Cluster II anomalies (PERF):

[7] See Stambaugh and Yuan (2017) for the details on the construction of each anomaly.

(7) Gross profitability (GP): Novy-Marx (2013) and Chen, Sun, Wei, and Xie (2018) show that firms with higher gross profits to assets earn higher risk-adjusted returns. Novy-Marx argues that gross profitability is the cleanest measure of true economic profitability due to low accounting manipulations.

(8) Return on assets (ROA): Fama and French (2006), Hou, Xue, and Zhang (2015), and Chen et al. (2018) find that firms with higher profitability or higher return on assets subsequently earn higher risk-adjusted returns.

(9) Medium-term momentum (MOM): Jegadeesh and Titman (1993) find that firms performing well in the past 3 to 12 months continue to perform well in the next 3 to 12 months. They further find that the strategy based on the past six month returns, skipping one month and holding for the next six months, is the most profitable.

(10) Financial distress 1 (Distress): Rational theory predicts that firms with higher financial distress risk should earn higher returns to compensate for the risk. However, Campbell, Hilscher, and Szilagyi (2008) and others find that firms with higher bankruptcy probability earn lower risk-adjusted returns. The bankruptcy probability is estimated from a dynamic logit model based on both accounting and equity market information.

(11) Financial distress 2 (O-score): Campbell et al. (2008) and others find that using the Ohlson (1980) O-score as the distress measure produces similar results. The O-score is estimated from a static model using accounting data alone.

In addition, several recent studies examine a growing set of anomalies to shed further light on the sources of cross-sectional return predictability. Harvey, Liu, and Zhu (2016) develop a multiple hypothesis-testing framework and apply it to more than 300 factors. They conclude that most of the anomalies or factors discovered previously are probably false. Green, Hand, and Zhang

(2017) find that only a small set of characteristics out of 94 are reliably independent determinants of cross-sectional expected returns in non-microcap stocks, and return predictability sharply falls after 2003. Similarly, McLean and Pontiff (2016) find that the return predictability of 97 variables shown to predict cross-sectional stock returns declines significantly following relevant publications, suggesting that investors learn about mispricing from academic studies. However, Yan and Zheng (2017) evaluate 18,000 fundamental signals from financial statements and show that many signals are significant predictors of cross-sectional stock returns even after accounting for data mining. They suggest that anomalies are better explained by mispricing. Engelberg, McLean, and Pontiff (2018a) show that anomaly returns are many times higher on earnings announcement dates, suggesting that anomalies are the result of investors' biased beliefs that are partially corrected by the arrival of information. All of these large-scale anomaly studies contribute to our understanding of whether the abnormal returns documented in previous studies are compensation for systematic risks, evidence of market inefficiency, or simply the result of extensive data mining.

2.2. Usefulness and biases of analyst research

Analysts are prominent information intermediaries in capital markets. They engage in private information acquisition, perform prospective analyses aimed at forecasting a firm's future earnings and cash flows, and conduct retrospective analyses that interpret past events. Regulators and other market participants view analysts' activities and competition between them as enhancing the informational efficiency of security prices. Analysts' important role in capital markets has spurred research showing that they influence the informational efficiency of capital markets.

A longstanding question in the literature concerns whether security analysts' research is useful for market participants. Early studies using short-run event windows to measure market reactions usually find that analyst forecasts and recommendations elicit large announcement returns. Elton, Gruber, and Grossman (1986) and Womack (1996) show that firms that receive buy (sell) recommendations tend to earn higher (lower) abnormal returns in the subsequent one to six months. Barber et al. (2001) extend the investigation to consensus recommendations. They show the potential to earn higher returns by buying the most highly recommended stocks and short selling the least favorably recommended stocks. Jegadeesh et al. (2004) find that the level of consensus recommendations adds value only to stocks with favorable quantitative characteristics and that the change in consensus recommendations is a more robust return predictor.

However, recent studies have shown that analysts' employment incentives create predictable biases in their research outputs and coverage decisions.[8] For example, McNichols and O'Brien (1997) report that the distribution of analysts' buy/sell recommendations is positively skewed because analysts are averse to conveying negative signals. La Porta (1996) finds that analysts over-extrapolate past growth trends and that their forecasts of long-term growth rates negatively predict stock returns, which contributes to the value premium. Jegadeesh et al. (2004) provide evidence that analyst recommendations are positively associated with some accounting, valuation, and growth characteristics that are negatively associated with future returns.

Drake, Rees, and Swanson (2011) find that short sellers often trade against analyst recommendations and that these trades are highly profitable. Analyst incentives to misinform, combined with mounting evidence of market inefficiency with respect to analyst reports (i.e., the market's fixation on or under- or overreaction to analyst reports), imply that analyst research

[8] See, for example, Womack (1996), Bradshaw (2004), and Groysberg, Healy, and Maber (2011).

cannot unambiguously be interpreted as serving to enhance the informational efficiency of capital markets. Specifically, analysts employed by brokerage houses that are affiliated with covered firms through an underwriting relationship issue more optimistic recommendations, earnings forecasts, and long-term growth forecasts than do unaffiliated analysts.[9] They are also less likely to reveal negative news.[10]

Finally, several recent studies have argued that the number of analysts covering a firm is an informative signal for future firm fundamentals and stock returns (Das, Guo, and Zhang, 2006; Jung, Wong, and Zhang, 2014; Lee and So, 2017). A typical security analyst faces non-trivial switching costs when making coverage decisions. Given their incentive structures, analysts' choices of which firms to cover should reflect their true expectation of firms' future performance.

2.3. Market participants and capital market anomalies

The existence and persistence of well-documented stock return anomalies have spurred a growing interest in investigating the underlying causes. Several recent papers argue that institutional investors and mutual funds in particular, through their correlated trading behavior, can contribute to the pervasiveness of these anomaly patterns. Jiang (2010) argues that herding among institutional investors contributes to the value effect. Edelen et al. (2016) find that institutional investors tend to trade in a direction contrary to anomaly prescriptions and that their trading amplifies anomaly returns. Akbas, Armstrong, Sorescu, and Subrahmanyam. (2015) find that aggregate flows into the mutual fund sector exacerbate well-known stock return anomalies, while aggregate flows into the hedge fund sector attenuate anomalies.

[9] See, for example, Dugar and Nathan (1995), Lin and McNichols (1998), and Dechow, Hutton, and Sloan (2000).

[10] See, for instance, O'Brien, McNichols, and Lin (2005).

With the tremendous growth of the hedge fund sector over the last decade, studies have begun to examine the relation between the trading behavior of these sophisticated investors and anomalies. Using short interest as a proxy for arbitrage capital, Hanson and Sunderam (2014) find that an increase in arbitrage capital on the anomalies has resulted in lower strategy returns. Chen, Da, and Huang (2018) propose a measure of net arbitrage trading based on the difference between abnormal hedge fund holdings and abnormal short interest on a stock. They find that anomaly returns come exclusively from the stocks traded by arbitrageurs. Anginer, Hoberg, and Seyhun (2015) show that the return predictability of anomalies disappears when insider trading disagrees with the anomalies.

3. Data and summary statistics

Analyst consensus recommendation data come from the I/B/E/S summary file, while the individual analyst recommendations are from the I/B/E/S detailed history file. The I/B/E/S detailed recommendation data begin in December 1992, and consensus recommendations start from 1993. Recommendation value (Rec) is coded as a number from 5 (strong buy) to 1 (strong sell). We also construct the change of consensus recommendations (ΔRec), as Jegadeesh et al. (2004) find that recommendation changes are more informative than recommendation levels. The recommendation change is calculated as the current consensus recommendation minus its value for the same firm one year ago. We merge the analyst data with Center for Research in Security Prices data after eliminating firms with share codes other than 10 or 11 and firms with stock prices below one dollar.

Following Stambaugh and Yuan (2017), we construct anomaly variables at the end of each month *t*. For the anomaly variables requiring annual financial statements from Compustat, we require at least a four-month gap between the portfolio formation month and the end of the fiscal year. For the quarterly reported earnings, we use the most recent data in which the earnings announcement date (RDQ in Compustat) precedes month *t*. For the quarterly balance sheet items, we use the data from the prior quarter.

We construct anomaly portfolios as follows. We sort all of the stocks into quintile portfolios based on each of the anomaly characteristics at the end of each month, and we define the long and short legs as the extreme quintiles. When constructing the composite mispricing scores, we require a stock to have a non-missing value at the end of month t - 1 for at least three of the anomalies to be included in that composite mispricing measure. For an anomaly to be included in the composite mispricing measure at the end of month t - 1, we also require at least 30 stocks to have non-missing values for that anomaly.

For each individual analyst, we also calculate the rank correlation between stocks' recommendation values and composite mispricing scores, $Corr_{MGMT}$ and $Corr_{PERF}$, using all recommendations issued by an analyst over the last three years. Specifically, in each month, we sort stocks into quintiles based on the two composite mispricing scores, where the highest (lowest) quintile represents the most undervalued (overvalued) stocks. Then, for each individual analyst i at the end of each year t, we calculate the rank correlation between stocks' anomaly rankings and recommendation values, using all recommendations issued by this analyst over the last three years as follows:[11]

$$Corr_{i,type,t} = \frac{\sum_{n=1}^{N}\left(Rec_{i,n,t} - \overline{Rec}_{i,t}\right)\left(Rank_n^{type} - \overline{Rank}^{type}\right)}{\sqrt{\sum_{n=1}^{N}\left(Rec_{i,n,t} - \overline{Rec}_{i,t}\right)^2 \sum_{n=1}^{N}\left(Rank_n^{type} - \overline{Rank}^{type}\right)^2}}, \tag{1}$$

[11] We only keep the latest recommendation of an analyst for each stock in a month. We include those analysts who issue at least three recommendations over the last three years in our sample.

where $type$ stands for the anomaly type, MGMT or PERF. $Rec_{i,n,t}$ is the value of the n^{th} recommendation issued by analyst i within the last three years before the end of year *t*, ranging from 1 (least favorable) to 5 (most favorable). *N* is the total number of recommendations issued by analyst *i* over the three-year period. $\overline{Rec}_{i,t}$ is the mean value of all recommendations issued by analyst *i* within the three years before the end of year *t*. $Rank_n^{type}$ is a quintile ranking variable (with a higher value indicating more underpricing) for the stock associated with the n^{th} recommendation, based on the composite mispricing score (MGMT or PERF) measured in the same month as when the n^{th} recommendation is issued.

We also construct variables proposed in the literature that are associated with the informativeness of analyst research, including analyst, recommendation, broker, and firm characteristics. Following Green, Jame, Markov, and Subasi (2014), we use $|\Delta Rec_{individual}|$ to measure the magnitude of individual analysts' recommendation changes. Kecskés, Michaely, and Womack (2016) find that stock recommendations accompanied by earnings forecast revisions lead to larger price reactions. We thus add a dummy variable, $Concurrent\ Rec$, that equals one if the analyst issues a forecast revision and a recommendation change for the same stock in the three trading days surrounding the forecast revision date and the recommendation change is in the same direction as the forecast revision. Ivkovic and Jegadeesh (2004) find that recommendations before (after) an earnings announcement lead to greater (weaker) price reaction. To control for these effects, we create a $Pre\text{-}earnings$ ($Post\text{-}earnings$) dummy variable that equals one if the recommendation is issued within two weeks prior to (after) the earnings announcement date and zero otherwise. $Away\ from\ consensus$ is a dummy variable that equals one if the absolute deviation of the recommendation change from the consensus is larger than the absolute deviation of the prior recommendation from the consensus. This is motivated by Gleason and Lee (2003) and Jegadeesh and Kim (2010), who find that analyst earnings forecast revisions or recommendation changes that move away from the consensus (i.e., bold forecasts) generate larger price impacts.

Regarding analyst characteristics, Stickel (1991) documents that recommendation changes made by all-star analysts have greater price impacts. Hence, we add a dummy variable $AllStar$ that equals one if the analyst is ranked as an All-American (first, second, third, or runner-up teams) in *Institutional Investor* magazine and zero otherwise. Loh and Mian (2006) show that analysts with more accurate earnings forecasts issue recommendations that are more profitable. We therefore control for *Accuracy*, which is the difference between the absolute forecast error of analyst *i* on firm *j*'s earnings and the average absolute forecast error across all analysts on firm *j*, scaled by the average absolute forecast error across all analysts' forecasts on firm *j*'s earnings. We then multiply this value by -1 and average across all stocks covered by an analyst in a given year, so that a higher value indicates that the analyst is on average more accurate. Mikhail, Walther, and Willis (1997) emphasize the importance of analyst experience for forecast accuracy. We thus construct two experience measures: $Ln(FirmExp + 1)$ ($Ln(TotalExp + 1)$) is the natural logarithm of one plus the number of days since the analyst first issued an earnings forecast for this firm (any firm). $Ln(BrokerSize)$ is the natural logarithm of the total number of analysts working for the brokerage company in a given year. This is to control for differences in the level of resources available to analysts employed by brokerage firms of different sizes (Clement, 1999). $Average\ Size$ is the average $Ln(Size)$ of stocks followed by an analyst in a given year. $Coverage$ is the total number of firms followed by an analyst in a given year.

Finally, we include several firm characteristics related to recommendation announcement returns. $Ln(Size)$ is the natural logarithm of firm market capitalization. $Volatility$ is the standard deviation of daily returns over the 63 trading days prior to the recommendation change. $MOM_{(-21,-1)}$ is the cumulative stock returns over the 21 trading days prior to the recommendation change. $MOM_{(-252,-22)}$ is the cumulative stock returns over the 252 trading days prior to the recommendation change, excluding the 21 trading days prior to the recommendation change.

Table 1 presents the summary statistics for the sample, including the number of observations and the mean, median, standard deviation, and the 25th and 75th percentiles of the main variables used in the analysis. In general, these summary statistics are consistent with the literature. The mean value of Rec is 3.85 and the median is 3.89, suggesting an overall optimism in analyst consensus recommendations (otherwise, both values should be close to 3). The mean of ΔRec is positive (0.04) in our sample, suggesting that analysts are more likely to upgrade than to downgrade a firm. Finally, $Corr_{MGMT}$ is on average negative, while $Corr_{PERF}$ is positive, suggesting that analysts use the information in different types of anomalies differently.

[Insert Table 1 here]

4. Empirical results

4.1. Informativeness of anomaly signals

In this section, we construct the 11 prominent asset-pricing anomalies and examine the unconditional anomaly returns using the sample overlapped with analyst consensus recommendation data from the I/B/E/S. We also construct two composite mispricing factors (MGMT and PERF) that combine the information of two clusters of anomalies.

Table 2 reports the monthly raw returns and the Fama and French three-factor alphas of long-short portfolios sorted by 11 anomalies and two composite mispricing factors. The *t*-statistics reported in parentheses are based on Newey-West (1987) standard errors with the optimal lag length.[12] Panel A (Panel B) reports the raw returns of the MGMT (PERF) anomalies, and Panel C (Panel D) reports the corresponding Fama and French three-factor alphas. Overall, long-short portfolios based on the 11 anomalies all generate significant Fama and French three-factor alphas ranging from 0.35% to 1.09% per month. The result suggests that anomalies contain valuable information about future expected returns, of which sophisticated information intermediaries, such as analysts, should take advantage. In addition, for most anomalies, the short leg generates much stronger abnormal returns than the long leg, consistent with evidence in the literature that short selling overvalued stocks is more prohibitive and costly than taking long positions on undervalued stocks (Nagel, 2005; Stambaugh et al, 2012).

[Insert Table 2 here]

4.2. Analyst recommendations around the anomalies

In this section, we examine whether analysts use anomaly information when making recommendations. We first sort all of the stocks into quintile portfolios based on their anomaly characteristics, and we then test the difference in the mean values of analyst consensus recommendations between the long and short legs of the portfolios. We analyze both the level and change of recommendations across the anomaly-sorted quintile portfolios. As recommendations might be persistent over time, we calculate the *t*-statistics for the differences in recommendations between the long and short legs of the anomalies based on Newey-West standard errors with the optimal lag length.[13]

[12] In the remainder of the paper, all *t*-statistics with stock returns as the dependent variable are based on the Newey-West standard errors with the optimal lag length.

[13] As a robustness check, we also calculate the *t*-statistics based on standard errors double clustered by stock and month (Petersen, 2009). Specifically, we run a panel regression, where the dependent variable is the level or change

Table 3 reports the results. In Panel A (Cluster 1), stocks in the short leg of the anomalies receive more favorable recommendations than those in the long leg of the anomalies. For example, the average recommendation value is 3.52 for the long leg of MGMT and 4.07 for its short leg. The difference of -0.55 is highly significant at the 1% level (*t*-stat = -13.47). We find similar results across all individual anomalies in the MGMT category. Indeed, the level (and change) of recommendations monotonically increases from the long leg to the short leg for almost all of the anomalies in the MGMT category. However, the anomalies in the PERF category display a different story. Analysts on average seem to issue recommendations in line with these anomalies' predictions. The mean recommendation level is 3.89 for the long leg of PERF and 3.71 for its short leg. The difference of 0.18 (*t*-stat = 5.62) is statistically significant but economically small compared with the difference of recommendations across portfolios sorted by MGMT anomalies.

[Insert Table 3 here]

The results are similar when we examine the change of recommendations. For anomalies in the MGMT category, analysts are more likely to upgrade stocks in the short leg and downgrade firms in the long leg of the portfolios. For example, analysts downgrade recommendations by 0.06 for the long leg of MGMT and upgrade recommendations by 0.02 for the short leg. The difference (-0.08) in the change of recommendations between long- and short-leg stocks is again highly significant (*t*-stat = -9.48), although small. The result for the change of recommendations is particularly puzzling because it suggests that while analysts actively issue opinions on anomaly

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of consensus recommendations for each stock-month, and the independent variables are dummies indicating the quintile portfolio category to which each stock belongs (except for the short-leg portfolio, which is omitted). Using this regression approach, we then report the estimated coefficient and corresponding *t*-statistic for the dummy variable indicating the long-leg portfolio. The results remain largely unchanged, and most *t*-statistics are still highly significant.

stocks, their opinions tend to be in the opposite direction to the anomaly predictions. Thus, analyst inattention and stale recommendation stories cannot fully explain our finding.

Overall, our results suggest that analysts tend to issue more favorable recommendations to stocks with high investment growth and large external financing needs but also to those with higher profitability and better recent stock performance. As firms with high investment rates and financing activities have lower expected returns, the result suggests that analysts on average do not fully use the expected return information contained in anomalies when making stock recommendations.

4.3. Anomaly returns conditional on analyst recommendations

The inconsistency between analyst recommendations and anomaly ranking presented in the previous section is not sufficient to conclude that analyst recommendations are biased. Given that analysts may have superior private information beyond that contained in anomaly characteristics, the information content of their recommendations may offset the information in the anomalies. To distinguish the two competing views of analyst research, we must examine ex post anomaly returns conditional on whether analyst recommendations confirm or contradict the anomaly signals.

To test this, we conduct independent double sorts of all stocks based on the anomaly signals and the level of recommendations. At the end of each June, we sort all stocks into three groups based on the level of consensus recommendations and independently into quintiles based on anomaly characteristics. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendation values. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. We then take the intersection of the two extreme quintiles of each anomaly with three terciles of recommendations. We then calculate the Fama and French three-factor alphas for each of the six portfolios. We further construct two types of long-short portfolios: one for which analyst recommendations are congruent with the anomaly prescriptions (Long/Up – Short/Down) and another for which recommendations are contradictory to the anomaly predictions (Long/Down – Short/Up). We also test the difference in the long-short portfolio returns between the inconsistent and consistent groups.

The Fama-French alphas and their corresponding *t*-statistics are reported in Table 4. The long-short portfolio alphas are larger for inconsistent portfolios than for consistent portfolios for all 11 anomalies, and seven of them are statistically significant. The result is particularly strong for anomalies in the PERF category. For example, the long-short portfolio based on PERF generates a monthly three-factor alpha of 1.57% for the inconsistent case, while it is only 0.90% for the consistent case. The difference in alphas between the inconsistent and consistent groups is 0.67%, with a *t*-statistic of 2.96. The results from individual anomalies in the PERF group are similar, with the differences in alphas between the inconsistent and consistent groups ranging from 0.43% to 0.65%, all of which are statistically significant. This suggests that although analysts tend to issue recommendations that are on average weakly consistent with performance-related anomalies, the stocks on which they make "mistakes" according to anomaly signals generate particularly large abnormal returns, especially on the short leg. The results suggest that analysts' biased recommendations might amplify performance-related anomalies.

[Insert Table 4 here]

For MGMT-related anomalies, we know from Table 3 that analyst recommendations on average tend to be contradictory to the prescriptions of anomalies. However, compared to PERF-related anomalies, although the differences in alphas between the inconsistent and consistent groups are all positive, they are much smaller and mostly insignificant, except in two cases: 0.54%

(*t*-stat = 2.34) for Accrual and 0.51% (*t*-stat = 2.41) for IA. However, if we focus on the short-leg portfolios, the amplification effect of biased recommendations on anomaly returns is also evident for those anomalies in the MGMT category. For example, the difference in the alphas of the short-leg portfolios between the inconsistent and consistent groups is -0.39% (-0.83% – (-0.44%)), with a *t*-statistic of -2.09 (not shown), for MGMT.[14] For comparison, the corresponding difference in alphas of the short-leg portfolios is -0.59% (= -1.09% – (-0.50%)), with a *t*-statistic of -2.92 (not shown), for PERF.

The preceding results suggest that a much smaller and largely insignificant return spread between inconsistent and consistent groups for MGMT-related anomalies must come from the offsetting effect in the long leg. This is indeed the case for MGMT, in which the consistent group actually outperforms the inconsistent group by 0.23% (= 0.40% – 0.17%). For PERF, the long-leg result is more in line with our hypothesis, in that the consistent group slightly underperforms the inconsistent group. The above observations are also evident for most individual anomalies.[15,16]

[14] Moreover, the differences in the alphas of short-leg portfolios between the inconsistent and consistent groups are all positive (ranging from 0.18% to 0.57%) and significant for four out of the six MGMT-related individual anomalies.

[15] We also notice that for some anomalies, there is a moderate hump-shaped relation between recommendation values and stock returns for the short leg of anomalies. We therefore conduct a formal test and find only one case (Distress) in which the *t*-statistic for the difference in alphas between Down and Middle recommendations in the short-leg portfolios is greater than 2.

[16] We also examine the earnings announcement returns of the consistent and inconsistent portfolios double sorted by analyst recommendations and anomalies. The results of the untabulated analysis are broadly consistent with, although weaker than, the results reported in Table 4.

Another approach complementary to portfolio sorts is to run Fama-MacBeth regressions of future stock returns (in percentage) on anomaly characteristics interacted with analyst recommendations. The regression approach allows us to control for other firm characteristics commonly associated with cross-sectional stock returns. Firm size ($Ln(Size)$) is the natural logarithm of market capitalization at the end of June in each year. Book-to-market ratio ($Ln(BM)$) is the natural logarithm of the most recent fiscal year-end reported book value divided by the market capitalization at the end of the prior calendar year. The short-term reversal measure (Rev) is the prior month's return. Idiosyncratic volatility ($IVOL$) is the standard deviation of the residuals from the regression of daily stock excess returns on the Fama and French three-factor returns over the previous month (Ang, Hodrick, Xing, and Zhang, 2006). $Turnover$ is the monthly trading volume over shares outstanding, averaged over the past 12 months. Analyst forecast dispersion ($Disp$) is the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast. $MaxReturn$ is a stock's maximum daily return the previous month (Bali, Cakici, and Whitelaw, 2011).

In addition, to preserve as many stock-month observations as possible, we replace the missing value of a control variable with its cross-sectional monthly median value, and we include a dummy variable $Missing$ that equals one if there is at least one missing value for any of the control variables and zero otherwise.[17] To facilitate the interpretation of regression coefficients, at the end of each June, we rank stocks into five groups based on anomalies and create three dummy

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[17] Our sample will be reduced by 20-30% if we do not fill in the missing values of control variables. However, our untabulated analysis shows that our main conclusion still holds using a smaller sample by excluding $Dispersion$ (which is insignificant in any model specification), which is the main driver for the reduction of stock-month observations.

variables, $Long$, $Short$, and Mid, which represent the long leg, the short leg, and the remaining three middle quintile portfolios, respectively. We also sort the stocks into three groups of equal size based on analyst consensus recommendations, with the most favorable (unfavorable) recommendation denoted as $RecUp$ ($RecDown$) and the middle group as $RecMid$. We run the Fama-MacBeth regression as follows:

$$\begin{aligned} Ret_{i,t+1} = \alpha &+ \beta_1 Long \times RecUp + \beta_2 Long \times RecMid + \beta_3 Long \times RecDown \\ &+\beta_4 Short \times RecUp + \beta_5 Short \times RecMid + \beta_6 Short \times RecDown + \\ &\beta_7 Missing + \sum \beta_k X_{k,i,t} + \epsilon_{i,t+1}. \end{aligned} \tag{2}$$

$X_{k,i,t}$ represents a set of control variables, $Ln(Size)$, Rev, $Ln(BM)$, $IVOL$, $Turnover$, $Disp$, and $MaxReturn$. Panel A of Table 5 reports the results for the MGMT-related anomalies and Panel B for PERF-related anomalies. Overall, the results using the Fama-MacBeth regression are similar to those of our portfolio sorts. The amplification effect of analyst recommendations on anomaly returns is most pronounced in the short leg. By comparing the coefficients of two interaction terms, $Short \times RecUp$ and $Short \times RecDown$, we find that the short-leg stocks experience the most negative future returns when those stocks are recommended the most favorably by analysts for all cases. For example, column (1) of Panel A shows that the estimated coefficient is -0.81 (*t*-stat = -6.19) for $Short \times RecUp$ and -0.58 (*t*-stat = -3.68) for $Short \times RecDown$ for MGMT. The result suggests that stocks in the short leg of MGMT with the most favorable recommendations underperform those with the most unfavorable recommendations by 0.23% per month after controlling for other return predictors. Similarly, column (1) of Panel B shows that stocks in the short leg of PERF generate a 1.04% (*t*-stat = -4.67) lower return when they have the most favorable recommendations, while it is 0.55% (t-stat = -3.53) for stocks with the most unfavorable recommendations, with an underperformance of 0.49% for the former.[18]

[Insert Table 5 here]

4.4. Corroborating evidence from the change of mutual fund ownership

The amplification effect of biased analyst recommendations on anomaly returns suggests that some investors who follow analyst opinions or think like analysts trade in the same direction as recommendations over the portfolio formation window.[19] Investors' excess demand leads to

[18] The Fama-MacBeth regression results also show a moderate hump-shaped relation between recommendation values and stock returns for the short leg of anomalies for some cases, as in portfolio sorts. A potential explanation might be that for overvalued stocks, unfavorable recommendations are more likely to reflect analysts' true opinion of the stocks and be less associated with their behavioral bias. In other words, the most unfavorable recommendations could be more informative than the middle-category recommendations (Asquith, Mikhail, and Au, 2004). As a result, two forces affect the overvalued stocks with the most unfavorable recommendations. First, investors are more likely to sell (or less likely to buy) stocks with unfavorable recommendations, facilitating the correction of overvaluation. Second, due to the incremental valuable information contained in unfavorable analyst recommendations, these stocks could be of lower quality and more overpriced compared to similarly overvalued stocks but with middle-category recommendations. We conduct a formal test and find only two cases (CEI and Distress) in which the t-statistics for the difference in the estimated coefficients between $Short \times RecMid$ and $Short \times RecDown$ are greater than 2.

[19] The channel we propose here requires investors to have enough time to react to analyst recommendations and create amplified (or reduced) mispricing for inconsistent (or consistent) recommendations. Hence, it is important to verify whether prevailing analyst recommendations from some time before the construction of anomalies are also inconsistent with anomaly signals. To test this, we examine analyst recommendations available at month t-3 for quintile portfolios sorted by anomalies constructed at month t. The results, reported in Table A1 in the Online Appendix, show that the analyst recommendation patterns are very similar to those reported in Table 3. That is, analyst recommendations prevailing one quarter before the construction of the anomaly portfolios are largely inconsistent with anomaly predictions for MGMT-related anomalies, while analyst recommendations/changes available one

further mispricing. Anomaly returns are thus amplified as prices subsequently revert to fundamental value.[20] To verify the channel, we use the change of mutual fund stock ownership[21] over the portfolio formation window (July of year *t*-1 to June of year *t*) to measure investors' demand on a stock.[22] We calculate the average mutual fund net buys over the portfolio formation window for the portfolios double sorted by analyst recommendations and anomaly signals, similar to Table 4. For both the long and short legs of anomaly portfolios, we also report the differences in mutual fund net buys between stocks with the most favorable and most unfavorable recommendations.

Table 6 reports the results. It clearly shows that analyst consensus recommendations are positively correlated with changes in mutual fund demand. For both the long and short legs of anomaly portfolios, stocks with the most favorable recommendations have significantly larger mutual fund net buys over the portfolio formation window compared with stocks with the most unfavorable recommendations. For MGMT, the short-leg portfolio with the most favorable analyst recommendations has mutual fund net buys of 3.86% over the portfolio formation window, while the same short-leg portfolio with the most unfavorable recommendations has mutual fund net buys

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quarter before are more consistent with the prescriptions of PERF-related anomalies. We also find similar results for analyst recommendations available at month *t*-1 rather than month *t*-3 (available upon request).

[20] We thank the referee for suggesting this potential channel and for all of the tests conducted in this subsection underline the amplification effect of biased analyst recommendations on anomaly returns.

[21] Mutual fund ownership of a stock is defined as the sum of shares held by mutual funds from Thomson Reuters Mutual Fund holdings database (S12) each quarter scaled by total shares outstanding.

[22] We focus on mutual fund trading for two reasons. First, in the U.S., mutual funds are important stock market players and their collective trading activities are large enough to have a price impact (Lou, 2012). Second, previous studies (Brown et al., 2013) show that mutual funds tend to herd with analysts' consensus recommendations.

of only 0.91%. The difference in mutual fund net buys between the two groups is 2.95% (*t*-stat = 7.16). As a benchmark, Table 1 shows that the unconditional mean and standard deviation of mutual fund net buys are 1.47% and 5.63%, respectively. We observe similar patterns for PERF and all 11 individual anomalies. Moreover, the effect of analyst recommendations on mutual fund net buys is more pronounced for the stocks in the short leg of the anomaly, in line with the pattern in portfolio return results (also mainly coming from the short leg). We also observe that the price run-up effect, as measured by the buy-and-hold cumulative abnormal returns (CARs) over the entire portfolio formation period, corroborates the mutual fund net buy effect.[23] The results are reported in Table A2 in the Online Appendix.

We have conducted several robustness checks for the mutual fund trading test. First, we use the average mutual fund net buys in the Fama-French 30 industries and the 5×5 size and book-to-market double-sorted portfolios as the benchmarks to adjust stock-level mutual fund net buys. Second, we use institutional net buys from all 13F institutions to measure investor demand. Our results remain unchanged. These results are not reported for brevity, but they are available upon request.

[Insert Table 6 here]

We further examine the lead-lag relationship between analyst recommendations and subsequent mutual fund net buys to shed light on the causal effect of analyst recommendations on stock anomalies. As mutual fund holdings are only observable at a quarterly frequency, we test whether analyst recommendations in March of year *t* affect mutual fund demand changes over the next quarter (from the end of March to the end of June of year *t*). Specifically, we calculate mutual

[23] The CAR is calculated as the individual stock buy-and-hold cumulative return minus the cumulative value-weighted market index return, averaged at the portfolio level.

fund net buys for portfolios sorted by both anomaly characteristics (at the end of June of year *t*) and consensus recommendations. To ensure that mutual fund net buys follow analyst recommendations, we conduct portfolio sorts based on the prevailing recommendation values at the end of March of year *t*.

The results, reported in Table A3 in the Online Appendix, show that analyst consensus recommendations indeed drive changes in mutual fund demand. For both the long leg and the short leg of anomaly portfolios, stocks with the most favorable recommendations have significantly larger mutual fund net buys over the quarter following recommendations than stocks with the least favorable recommendations. For MGMT, the short-leg portfolio with the most favorable analyst recommendations has mutual fund net buys of 0.84% over the following quarter, while the same short-leg portfolio with the least favorable recommendations has mutual fund net buys of only 0.28%. The difference in mutual fund net buys between the two groups is 0.55% and is highly significant. We observe similar patterns for all 11 individual anomalies. Furthermore, for MGMT-related anomalies, the effect of analyst recommendations on mutual fund net buys is more pronounced for the short leg than for the long leg of anomaly portfolios. As a comparison, the difference in mutual fund net buys between the most and least favorably recommended stocks for the long leg of MGMT is only 0.33%.

If mutual funds' excess buying demand for short-leg stocks with favorable consensus recommendations amplifies mispricing, then these stocks should experience a greater price run-up than stocks with unfavorable recommendations. To test this implication, we calculate the CARs from April to June of year *t* for portfolios sorted by both anomalies and consensus recommendations. To ensure investors have sufficient time to react to analyst recommendations, we conduct portfolio sorts based on the prevailing recommendation values at the end of March of year *t* and the anomaly characteristics at the end of June of year *t*. For both the long leg and the short leg of anomaly portfolios, we also report the differences in CARs between stocks with the most and least favorable consensus recommendations.

Table 7 reports the results, which support our conjecture that the initial price run-up is more positive for stocks with favorable recommendations, explaining why we see return reversals after portfolio construction. For both the long leg and the short leg of anomaly portfolios, stocks with the most favorable recommendations have significantly larger CARs over the period April to June of year *t* than stocks with the least favorable recommendations for all cases. Moreover, for MGMT-related anomalies, the effect of analyst recommendations on the CARs is more pronounced for the short leg of anomaly portfolios for all individual anomalies and MGMT. For instance, for MGMT, the short-leg portfolio with the most favorable analyst recommendations has a CAR of 7.91% over the portfolio formation window, while the same short-leg portfolio with the least favorable recommendations has a CAR of only 0.14%. The difference in CARs between the two groups is 7.77% and is highly significant. In comparison, the difference in CARs between the two groups for the long leg of MGMT is only 4.83%. For PERF-related anomalies, except for GP, the price run-up patterns are similar, although weaker.

[Insert Table 7 here]

In sum, the mutual fund trading and price run-up results suggest that analyst recommendations lead to coordinated trading activities by mutual fund managers. Mutual fund managers' excess buying demand for overvalued stocks with favorable consensus recommendations pushes up stock prices further during the portfolio formation window, leading to lower subsequent returns.

4.5. Identifying skilled analysts based on the correlation between recommendations and anomalies

The results so far suggest that on average, analysts do not efficiently use the expected return information contained in anomalies when making recommendations, which prove to be inefficient ex post. This bias for analysts as a whole, however, may mask great heterogeneity among individual analysts who differ significantly in their skills and/or incentives to generate informative recommendations. We use the correlation measure based on Eq. (1) as a proxy for analyst skill. We then study which analysts tend to issue recommendations that are more consistent with anomaly predictions. Specifically, we run the following panel regression:

$$\begin{aligned} Corr_{s,i,t} = {} & \alpha + \beta_1 AllStar + \beta_2 Away\ from\ consensus + \beta_3 Accuracy + \\ & \beta_4 Ln(FirmExp + 1) + \beta_5 Ln(TotalExp + 1) + \beta_6 Ln(BrokerSize) + \\ & \beta_7 Coverage + \beta_8 Average\ Size + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $s \in \{MGMT, PERF\}$ and $Corr_{s,i,t}$ is the rank correlation between stocks' recommendation values and the composite mispricing score MGMT (or PERF), using all recommendations issued by analyst *i* over the last three years up to year *t*. All other variables are defined as before. We also control for analyst and year fixed effects in some specifications, and standard errors are double clustered by analyst and year.

Table 8 presents the regression results. Across different specifications, forecast accuracy is positively related to our correlation measures. Meanwhile, $Corr_{PERF}$ is also positively related to $AllStar$ and $Ln(BrokerSize)$, suggesting that star analysts and analysts working for larger brokerage firms are more likely to use performance-related anomaly information. However, for $Corr_{MGMT}$, we find the opposite results. Moreover, $Corr_{MGMT}$ is also positively associated with $Average\ Size$ and negatively associated with total experience. The finding of negative associations of brokerage firm size, all star status, and working experience with $Corr_{MGMT}$

suggests that analysts' biased recommendations for MGMT-related anomalies could be attributable to strategic reasons.

[Insert Table 8 here]

4.6. Market reactions to skilled analysts' recommendations

If anomaly signals are incrementally useful for identifying skilled or unbiased analysts, we expect the recommendations made by these analysts to elicit stronger market reactions. To test this, we run a panel regression of recommendation announcement returns on our correlation measures, controlling for recommendation, analyst, broker, and firm characteristics. Specifically, we run the following panel regression:

$$\begin{aligned} CAR[0,+1] = {} & \alpha + \beta_1 Corr_s + \beta_2 |\Delta Rec_{individual}| + \beta_3 All\ Star + \beta_4 Concurrent\ Rec + \\ & \beta_5 Pre\text{-}earnings + \beta_6 Post\text{-}Earnings + \beta_7 Away\ from\ consensus + \\ & \beta_8 Accuracy + \beta_9 Ln(Firm\ Exp + 1) + \beta_{10} Ln(Total\ Exp + 1) + \\ & \beta_{11} Ln(BrokerSize) + \beta_{12} Coverage + \sum \beta_k X_{k,i,t} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $CAR[0,+1]$ is the two-day cumulative abnormal returns (in percentage) around analyst recommendation announcements. $X_{k,i,t}$ represents a set of firm characteristics, including $Ln(Size)$, $Volatility$, $MOM_{(-21,-1)}$, and $MOM_{(-252,-22)}$. Other variables are defined as before.

Panel A of Table 9 reports the results for upgrade recommendation changes and Panel B for downgrade recommendation changes. The coefficient on $Corr_{PERF}$ is significantly positive for upgrade recommendation changes and significantly negative for downgrade recommendation changes. The coefficient on $Corr_{MGMT}$ is insignificant for upgrade and marginally significant for downgrade recommendation changes. The results suggest that the market perceives analysts who are better at using performance-related anomaly signals ($Corr_{PERF}$) as more skilled in general, and these analysts therefore elicit stronger market reactions.

The economic significance of our correlation metric is non-trivial. For example, the coefficient on $Corr_{PERF}$ reported in the last column of Panel A suggests that an analyst whose stock recommendations are perfectly aligned with PERF anomaly rankings ($Corr_{PERF}$ = 1) generates a two-day announcement return 0.4% higher than that of an analyst whose recommendations are unrelated to PERF anomaly signals ($Corr_{PERF}$ = 0). The result is even stronger for downgrade recommendation changes; Panel B shows that market reactions to downgrade recommendation changes of skilled analysts are 0.5% to 0.7% more negative than they are to those of unskilled analysts. The incremental effect of our analyst skill measure survives after controlling for firm and analyst fixed effects in the panel regressions. A significant coefficient on $Corr_{PERF}$ after controlling for analyst fixed effects means that an analyst's recommendation becomes more informative when she becomes more skilled at using performance-related anomaly information for her recommendations.

[Insert Table 9 here]

4.7. The market efficiency implications of skilled analysts

Given that the market recognizes the superior skill (measured by $Corr_{PERF}$) of analysts who exploit performance-related anomalies, why do the anomaly returns still exist?[24] Table 1 shows that the 75th percentile of $Corr_{PERF}$ is only 0.19. The 90th percentile of $Corr_{PERF}$ is 0.35 (not shown). The results suggest that skilled analysts who exploit anomalies when issuing recommendations make up only a small fraction of all analysts and that their existence may not fully eliminate mispricing. A recent paper by Birru, Gokkaya, and Liu (2018) provides evidence to support this conjecture. They show that sell-side analysts backed by quantitative research exhibit more efficient recommendation behavior toward anomaly predictors, and these analysts elicit

[24] We thank the referee for asking this insightful question.

stronger recommendation announcement returns. Importantly, they find that stocks followed by more quant-backed analysts have significantly attenuated anomaly returns. However, because such analysts represent only a small fraction of the sell-side analyst profession, their existence does not fully eliminate the return predictability of anomalies.

Following Birru et al. (2018), we conduct a test to show whether the existence of "skilled" analysts based on our measure $Corr_{PERF}$ can attenuate the return predictability of anomalies. Specifically, we first define skilled analysts as those who are in the top decile of the cross-section of all analysts with the highest correlation metric $Corr_{PERF}$. For each stock-month, we then compute a measure, $Coverage\_skill$, that captures the number of skilled analysts, scaled by the total number of analysts following the stock as follows:

$$Coverage\_skill = Ln\,[(1 + \#\, of\ skilled\ analysts)/(1 + \#\, of\ total\ analysts)]. \qquad (5)$$

We next run the Fama-MacBeth regression of monthly stock returns on the anomalies and their interactions with $Coverage\_skill$.[25] We also control for the interactions of anomalies with firm size and turnover. Table A4 in the Online Appendix reports the result. The coefficients on the interaction term between $Anomaly$ and $Coverage\_skill$ are significantly positive for the two composite mispricing measures and for six of the 11 individual anomalies (eight are positive). The positive coefficient on the interaction between $Anomaly$ and $Coverage\_skill$ means that stocks followed by a larger fraction of skilled analysts have a weaker return predictability associated with the anomaly. This result supports our conjecture that the existence of skilled analysts who exploit anomalies could potentially mitigate (but not eliminate) mispricing.

[25] We multiply anomaly characteristics by -1 for momentum, gross profitability, and return on assets, so that a higher value of an anomaly always indicates more overpricing.

5. Additional tests and explanations

5.1. *Results in the post-publication period*

A potential explanation for the contradiction between analyst recommendations and anomaly signals is that analysts are simply unaware of the information contained in anomalies before their discovery by academics. If this is true, analyst recommendations should become more aligned with anomaly predictions upon the publications of these anomaly studies (McLean and Pontiff, 2016). To examine this alternative, we redo the test by focusing on the post-publication period. Panel A of Table 10 shows the Fama-French three-factor alphas of the 11 anomalies in the post-publication period. Consistent with McLean and Pontiff (2016), anomalies are generally weaker in the post-publication period. The post-publication attenuation of anomaly returns is more pronounced for PERF-related anomalies than for MGMT-related anomalies. Of the 11 anomalies, only seven still generate positive alphas with *t*-statistics greater than 1.65, whereas three (all from PERF) actually generate negative alphas, with GP earning a significantly negative alpha of -0.44% (*t*-stat = -2.06).

[Insert Table 10 here]

Panel B of Table 10 reports the mean recommendation levels and changes for quintile portfolios sorted by each anomaly during the post-publication period. The results show that for all MGMT-related anomalies, analysts still assign more favorable recommendation values to stocks in the short leg than to stocks in the long leg of anomalies. Most MGMT-related anomalies still generate significant alphas in the post-publication period, suggesting that our findings are unlikely to be fully explained by analysts' unawareness of the return predictability of the anomalies.

5.2. *Effect of firm size*

The limits-to-arbitrage argument is often cited to explain why well-documented anomalies are not arbitraged away. According to this explanation, competition between sophisticated investors would quickly eliminate any return predictability arising from anomalies without impediments to arbitrage. This explanation is difficult to reconcile with our evidence, because analysts do not take positions and do not face trading frictions. Rather, our results suggest that analysts' biased recommendations could be a source of friction that impedes the efficient correction of mispricing. Still, analysts may need to cater to institutional investors who indeed face non-trivial trading frictions. Our findings may be concentrated among small and illiquid stocks, where analysts do not have strong incentives to efficiently use the information in anomalies simply because their institutional clients cannot trade on such stocks at a low cost.

To examine this explanation, we redo our main tests for small and big firms separately. If the limits-to-arbitrage explanation plays a role, we should find that analyst recommendations are more consistent with anomaly rankings among big stocks. We define small (big) stocks as those with market capitalization below (above) the 30% size cutoff using the NYSE size breakpoints. Panel A of Table 11 reports analyst recommendations across quintile portfolios sorted by anomalies for small and big firms separately. The general pattern is quite similar across small and big firms. For example, on average, analysts assign a recommendation value to the short leg of MGMT that is 0.54 higher than that assigned to the long leg among small stocks. For big stocks, this number is 0.53 and still highly significant. In other words, analysts tend to issue more favorable recommendations to stocks classified as overvalued, even among big firms where trading frictions are less severe.

[Insert Table 11 here]

Panel B of Table 11 shows that the degree to which biased analyst recommendations amplify anomaly returns does not differ significantly across small and big stocks. Take PERF as an example. The difference in the monthly alphas between inconsistent and consistent long-short portfolios is 0.74% (*t*-stat = 2.96) for small stocks and 0.60% (*t*-stat = 2.21) for big stocks. Overall, our results do not seem to support the alternative explanation that analysts are reluctant to use anomaly signals when making recommendations simply because of limits-to-arbitrage concerns.

As firm size could be a noisy proxy for trading frictions, we redo the subsample tests based on a trading cost measure where, following Chung and Zhang (2014), the trading cost is measured as the daily percentage quoted spread. The results are quite similar, as reported in Table A5 in the Online Appendix. Overall, even among stocks facing low trading costs, analyst recommendations are still largely inconsistent with anomaly predictions and in fact amplify anomaly returns.

5.3. Effect of institutional holdings

Studies have shown that institutional investors as a group tend to trade contrary to the prescriptions of stock anomalies. For example, institutions tend to buy growth stocks and sell value stocks (Frazzini and Lamont, 2008; Jiang, 2010). Edelen et al. (2016) examine the relation between several well-known stock anomalies and changes in institutional investors' holdings. They find that institutions tend to buy overvalued stocks and sell undervalued stocks. Therefore, analysts may issue biased recommendations mainly to cater to institutional investors' preferences for overvalued stocks. To examine this possibility, we run our baseline tests on subsamples divided by stocks' institutional ownership. Analysts' recommendations should be more biased for stocks held by more institutions according to this explanation.

Panel A of Table 12 reports analyst consensus recommendations across quintiles of anomaly-sorted portfolios for stocks with low and high institutional ownership separately. We define institutional ownership as the number of shares held by all 13F institutional investors over the total number of shares outstanding. The results show that analyst recommendations are similarly biased for both groups of stocks. Looking at high-institutional-ownership stocks, analyst recommendations for the short leg of MGMT are 0.54 higher than those for the long leg of MGMT. The corresponding difference is 0.53 for low-institutional-ownership stocks.

[Insert Table 12 here]

Panel B of Table 12 further shows that analysts' biased recommendations amplify anomaly returns to a similar degree for stocks with low and high institutional ownership. Take PERF as an example. The difference in long-short portfolio alphas between the inconsistent and consistent groups is 0.63% (t-stat = 1.98) for low-institutional-ownership stocks and 0.55% (t-stat = 2.37) for high-institutional-ownership stocks. Overall, the evidence is not in line with the alternative explanation that analysts issue biased recommendations mainly to cater to institutional investors' preferences.

In Table A6 in the Online Appendix, we conduct a similar subsample test based on stock ownership by long-horizon institutional investors, who are defined as "dedicated" 13F institutions, following the classification of Bushee (1998).[26] As most of our anomalies are based on annual accounting information and characterized by low portfolio turnover, long-horizon institutions may have a stronger distortionary effect on analysts' behavior. However, the results show that analyst

[26] According to Bushee (1998), dedicated institutions are characterized by large average investment in portfolio firms and extremely low turnover, consistent with a "relationship investing" role and a commitment to provide long-term patient capital.

recommendations are similarly biased for both groups of stocks, regardless of whether they are held largely by long-horizon institutions.

5.4. *Effect of investor sentiment*

Stambaugh et al. (2012) find that anomalies are more pronounced following high sentiment periods, suggesting that investors' over-optimism during high-sentiment periods drives anomaly returns. Hribar and McInnis (2012) find that analyst forecasts are more optimistic for hard-to-value stocks during high-sentiment periods. This suggests that analyst recommendations could be more biased and the amplification effect of analysts' biased recommendations on anomaly returns should be more pronounced during high- rather than low-sentiment periods. To test this conjecture, we use the Baker-Wurgler (2006) sentiment index as a proxy for the aggregate investor sentiment in the stock market. We define a month as a high-sentiment period if the Baker-Wurgler sentiment index over the previous month is above the median of the whole sample, and as a low-sentiment period otherwise.

Panel A of Table 13 reports the averages of analyst recommendation values across the quintiles of anomaly-sorted portfolios in low- and high-sentiment periods separately. Consistent with the *biased analyst hypothesis*, analyst recommendations are more contradictory to anomaly predictions during high-sentiment periods. Following low-sentiment periods, the difference in recommendation values between the short and long legs of MGMT is 0.48. Following high-sentiment periods, the corresponding difference increases to 0.59. Given the evidence that anomalies have stronger return predictability in high-sentiment periods (Stambaugh et al., 2012), analysts should follow anomalies more closely at such times if they are sophisticated and unbiased. However, we find exactly the opposite results, suggesting that over-optimism shared with other investors during high-sentiment periods causes analyst recommendations to be more contradictory to anomaly signals.

Panel B of Table 13 shows not only that analyst recommendations are more biased during high-sentiment periods but also that their biased recommendations amplify anomaly returns more strongly at such times. Take PERF as an example. The difference in the long-short portfolio alphas between the inconsistent and consistent groups is an insignificant 0.12% (*t*-stat = 0.40) during low-sentiment periods, while it is 0.99% (*t*-stat = 3.19) during high-sentiment periods. Overall, the subsample results based on the sentiment index suggest that behavioral bias on the part of analysts is partially responsible for analysts' inefficient use of anomaly information.

[Insert Table 13 here]

5.5. Other anomalies

So far, we have focused on the 11 prominent anomalies proposed by Stambaugh et al. (2012) to avoid cherry-picking anomalies. In this section, we examine whether our main results hold for six alternative prominent anomalies: idiosyncratic volatility (IVOL) (Ang et al., 2006), maximum daily returns (MaxReturn) (Bali et al., 2011), past 12-month turnover (Turnover) (Chordia, Subrahmanyam, and Anshuman, 2001), cash flow duration (Duration) (Weber, 2018), long-run reversal (LMW) (DeBondt and Thaler, 1985), and market beta (Beta) (Baker, Bradley, and Wurgler, 2011; Frazzini and Pedersen 2014). Various studies show that these anomalies are also associated with significant abnormal returns.

Table A7 in the Online Appendix reports the long-short portfolio returns of these alternative anomalies. Panel A reports the raw returns, and Panel B reports the Fama and French three-factor alphas. Overall, five of the six alternative anomalies generate significant Fama and French three-factor alphas for the long-short portfolio with t-statistics greater than 1.65, with monthly alphas ranging from 0.42% to 1.06%.

We then examine whether analysts take advantage of these anomalies when recommending stocks. Table A8 in the Online Appendix reports the level and change of the consensus recommendations for quintile portfolios sorted by each of the six anomalies. Our findings are pervasive across all six anomalies based on the level of recommendations. Stocks in the short leg of anomalies tend to receive more favorable recommendations than do stocks in the long leg. Table A9 in the Online Appendix further shows the results from independent double sorts based on the six anomaly signals and the level of analyst recommendations. Consistent with our previous analysis, when analyst recommendations are inconsistent with anomaly predictions, anomaly returns are significantly amplified. The inconsistent long-short portfolio generates a much larger alpha than the consistent portfolio for all six anomalies, and the differences in alphas are significant in five of the six anomalies. The consistent results obtained from these market-based anomalies further support our conclusion that analysts do not efficiently use anomaly information when making recommendations.[27]

5.6. Informativeness of analyst consensus recommendations

Jegadeesh et al. (2004) examine the informativeness of analyst consensus recommendations using recommendation data from Zacks from 1985 to 1998. Similarly, Barber et al. (2001) look at the investment value of consensus recommendations using Zacks data from 1985 to 1996. Their results show that stocks with favorable (upgraded) analyst recommendations outperform stocks

[27] Moreover, we do not find a clear hump-shaped relation between recommendation values and stock returns for the short leg of all six alternative anomalies reported in Table A10 in the Online Appendix.

with unfavorable (downgraded) recommendations, suggesting that analyst recommendations have investment value to investors. To reconcile their evidence with our finding that analyst consensus recommendations are inefficient on average, we reexamine the unconditional return predictability of analyst consensus recommendations using I/B/E/S data over the sample period from 1993 to 2014.

Specifically, at the beginning of each quarter, we sort stocks into quintiles based on the consensus recommendations (both the level and change of recommendations) observed at the end of the last quarter and rebalance the portfolio on a quarterly basis. Panels A and C of Table A10 in the Online Appendix report the raw returns and Fama-French three-factor alphas on the long-short portfolios, where we long stocks with the most favorable (upgraded) recommendations and short stocks with the most unfavorable (downgraded) recommendations. We also use monthly recommendation values and rebalance on a monthly basis; the corresponding results are reported in Panels B and D of Table A10.

Our results show that the level of recommendation is uninformative for future returns over various sample periods,[28] while the change of recommendations is more informative. However, the economic magnitude of the return predictability of the change of recommendations is relatively

[28] The fact that the unconditional return predictability of the recommendation level is insignificant is not necessarily inconsistent with the significant interaction effect we document in Table 4. Table 4 shows the results from portfolio double sorts based on both the recommendation level and anomaly signals and documents that overvalued stocks with the most favorable recommendations have large negative returns. However, these overvalued stocks represent only a fraction of the entire group of most favorably recommended stocks in Table A10 in the Online Appendix and hence may not have a discernible impact on the returns of this entire group. Untabulated analysis shows that in the group of most favorably recommended stocks, 31.45% and 18.44% of stocks are overvalued based on MGMT and PERF, respectively.

small. For example, Panel D of Table A10 shows that the monthly-rebalanced long-short portfolio generates a monthly alpha of 37 bps over the full sample period. However, analyst recommendations seem to be more informative in the early periods. The change of consensus recommendations generates a monthly alpha of 68 bps over the 1993-2000 period, while the alphas (12 to 15 bps) become insignificant in the 2001-2014 period.[29] Overall, we believe that the different results between our paper and Jegadeesh et al. (2004) are probably due to the different sample periods studied in these two papers.

6. Conclusion

In this paper, we examine the interaction effect between analyst recommendations and stock market anomalies. Our results reveal that analysts tend to give more favorable recommendations to stocks classified as overvalued (the short leg of an anomaly). Most importantly, both portfolio analysis and the Fama-MacBeth regression demonstrate that these overvalued stocks with the most favorable analyst recommendations earn particularly negative abnormal returns in the future. Further analysis shows that the amplification effect of biased analyst recommendations on anomalies is not driven by limits-to-arbitrage concerns or analysts catering to institutional investors' preferences. In contrast, we find that the amplification effect is more pronounced during high-sentiment periods than during low-sentiment periods, suggesting that analysts' behavioral biases, rather than misaligned incentives, could partially explain their overly optimistic recommendations for overvalued stocks. Overall, our findings indicate that analysts' biased

[29] Our subsample results are consistent with Altınkılıç, Hansen, and Ye (2016) in that analysts' recommendation revisions no longer predict future long-term returns in the recent information era.

recommendations could be a potential source of market friction that impedes the efficient correction of mispricing.

We make several contributions to the literature. First, our work sheds light on the persistence of stock return anomalies by showing that analysts' biased recommendations might be a potential force contributing to mispricing in the financial market. Second, our results add to the understanding of analysts' role as informational intermediaries, revealing that they do not fully use the valuable information contained in anomaly signals and often contradict anomaly prescriptions when making recommendations. Finally, we develop a simple method to identify skilled analysts based on the correlation between their stock recommendations and anomaly signals. We show its usefulness beyond the existing analyst skill and experience measures.

References

Akbas, F., Armstrong, W. J., Sorescu, S., Subrahmanyam, A., 2015. Smart money, dumb money, and capital market anomalies. Journal Financial Economics 118, 55–382.

Altınkılıç, O., Hansen, R. S., Ye, L., 2016. Can analysts pick stocks for the long-run? Journal of Financial Economics 119, 371–398.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61,259–276.

Deniz, A., Gerard, H., Nejat, S., 2015. Can anomalies survive insider disagreements? Unpublished working paper.

Asquith, P., Mikhail, M. B., Andrea, A. S., 2004. Information content of equity analyst reports. Journal of Financial Economics 75, 245–282

Bali, T. G., Cakici, N., Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427–446.

Baker, M., Brendan, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. Financial Analysts Journal 67, 40–54.

Baker, M., Jeffrey, W., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645–1680.

Barber, B. M., Lehavy, R., McNichols, M., Trueman, B., 2001. Can investors profit from the prophets? Security analyst recommendations and stock returns. Journal of Finance 56, 531–563.

Birru, J., Gokkaya, S., Liu, X., 2018. Capital market anomalies and quantitative research. Unpublished working paper.

Bordalo, P., Gennaioli, N., Porta, R. L., Shleifer, A., 2018. Diagnostic expectations and stock returns. Journal of Finance, forthcoming.

Bouchaud, J. P., Krueger, P., Landier, A. L., Thesmar, D., 2018. Sticky expectations and the profitability anomaly. Journal of Finance, forthcoming.

Bradshaw, M. T., 2004. How do analysts use their earnings forecasts in generating stock recommendations? The Accounting Review 79, 25–50.

Bradshaw, M. T., Richardson, S., Sloan, R., 2006. The relation between corporate financing activities, analysts' forecasts and stock returns. Journal of Accounting and Economics 42, 53–85.

Brown, N., Wei, K. D., Wermers, R., 2013. Analyst recommendations, mutual fund herding, and overreaction in stock prices. Management Science 60, 1–20.

Bushee, B. J., 1998. The influence of institutional investors on myopic R&D investment behavior. The Accounting Review 73, 305–333.

Bushee, B. J., Noe, C. F., 2000. Corporate disclosure practices, institutional investors, and stock return volatility. Journal of Accounting Research 38, 171–202.

Campbell, J. Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. Journal of Finance 63, 2899–2939.

Cen, L., Hillary, G., Wei, K. C. J., 2013. The role of anchoring bias in the equity market: Evidence from analysts' earnings forecasts and stock returns. Journal of Financial and Quantitative Analysis 48, 47–76.

Chen, S., Matsumoto, D. A., 2006. Favorable versus unfavorable recommendations: The impact on analyst access to management-provided information. Journal of Accounting Research 44, 657–689.

Chen, T-F., Sun, L., John, K. C. J., Xie, F., 2018. The profitability effect: Insights from international equity markets. European Financial Management 24, 545–580.

Chen, Y., Da, Z., Huang, D., 2018. Arbitrage trading: The long and the short of it. Review of Financial Studies, forthcoming.

Chordia, T., Subrahmanyam, A., Anshuman, V. R., 2001. Trading activity and expected stock returns. Journal of Financial Economics 59, 3–32.

Chung, K. H., Zhang, H., 2014. A simple approximation of intraday spreads using daily data. Journal of Financial Markets 17, 94–120.

Cowen, A., Groysberg, B., Healy, P., 2006. Which types of analyst firms are more optimistic? Journal of Accounting and Economics 41, 119–146.

Clement, M. B., 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? Journal of Accounting and Economics 27, 285–303.

Cooper, M. J., Gulen, H., Schill, M. J., 2008. Asset growth and the cross-section of stock returns. Journal of Finance 63, 1609–1651.

Daniel, K., Titman, S., 2006. Market reaction to tangible and intangible information. Journal of Finance 52, 1–33.

Das, S., Guo, R., Zhang, H., 2006. Analysts' selective coverage and subsequent performance of newly public firms. Journal of Finance 61, 1159–1185.

DeBondt, W. F. M., Thaler, R., 1985. Does the stock market overreact? Journal of Finance 40, 793–805.

Dechow, P., Hutton, A., Sloan, R., 2000. The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. Contemporary Accounting Research 17, 1−32.

Drake, M. S., Rees, L., Swanson, E. P., 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. The Accounting Review 86, 101–130.

Dugar, A., Nathan, S., 1995. The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations. Contemporary Accounting Research 12, 131–160.

Edelen, R., Ince, O. S., Kadlec, G. B., 2016. Institutional investors and stock return anomalies. Journal Financial Economics 119, 472–488.

Elton, E. J., Gruber, M. J., Grossman, S., 1986. Discrete expectational data and portfolio performance. Journal of Finance 41, 699–713.

Engelberg, J., McLean, R. D., Pontiff, J., 2018a. Anomalies and news. Journal of Finance 73, 1971–2001.

Engelberg, J., McLean, R. D., Pontiff, J., 2018b. Analysts and anomalies. Unpublished working paper.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E., French, K., 2006. Profitability, investment and average returns. Journal of Financial Economics 82, 491–518.

Fama, E., French, K., 2008. Dissecting anomalies. Journal of Finance 63, 1653–1678.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Frazzini, A., Pedersen, L. H., 2014. Betting against beta. Journal of Financial Economics 111, 1–25.

Frazzini, A., Lamont, O. A., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88, 299–322.

Gleason, C. A., Lee, C. M. C., 2003. Analyst Forecast Revisions and Market Price Discovery. The Accounting Review 78, 193–225.

Green, J., Hand, J. R. M., Zhang, X. F., 2017. The characteristics that provide independent information about average U.S. monthly stock returns. Review of Financial Studies 30, 4389–4436.

Green, T. C., Jame, R., Markov, S., Subasi, M., 2014. Access to management and the informativeness of analyst research. Journal of Financial Economics 114, 239–255.

Groysberg, B., Healy, P. M., Maber, D, A., 2011. What drives Sell-Side analyst compensation at High-Status investment banks? Journal of Accounting Research 49, 969–1000.

Hanson, S. G., Sunderam, A., 2014. The growth and limits of arbitrage: Evidence from short interest. Review of Financial Studies 27, 1238–1286.

Harvey, C. R., Liu, Y., Zhu, H., 2016. …and the cross-section of expected returns. Review of Financial Studies 29, 5–68.

Hirshleifer, D., Hou, K., Teoh, S. H., Zhang, Y., 2004. Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

Hribar, P., McInnis, J., 2012. Investor sentiment and analysts' earnings forecast errors. Management Science 58, 293–307.

Ivkovic, Z., Jegadeesh, N., 2004. The timing and value of forecast and recommendation revisions. Journal of Financial Economics 73, 433–463.

Jegadeesh, N., Kim, J., Krische, S. D., Lee, C. M., 2004. Analyzing the analysts: When do recommendations add value? Journal of Finance 59, 1083–1124.

Jegadeesh, N., Kim, W., 2010. Do analysts herd? An analysis of recommendations and market reactions. Review of Financial Studies 23, 901–937.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jiang, H., 2010. Institutional investors, intangible information, and the book-to-market effect. Journal Financial Economics 96, 98–126.

Jung, M. J., Wong, M. H. F., Zhang, X. F., 2014. Analyst interest as an early indicator of firm fundamental changes and stock returns. The Accounting Review 90, 1049–1078.

Kecskés, A., Michaely, R., Womack, K. L., 2016. Do earnings estimates add value to sell-side analysts' investment recommendations? Management Science 63, 1885–1871.

La Porta, R., 1996. Expectations and the cross section of stock returns. Journal of Finance 51, 1715–1742.

Lee, C. M. C., So, E. C., 2017. Uncovering expected returns: Information in analyst coverage proxies. Journal of Financial Economics 124, 331–348.

Lin, H. W., McNichols, M. F., 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics 25, 101−127.

Loh, R. K., Mian, G. M., 2006. Do accurate earnings forecasts facilitate superior investment recommendations? Journal of Financial Economics 80, 455−483.

Lou, D., 2012. A flow-based explanation for return predictability. Review of Financial Studies 25, 3457–3489.

Loughran, T., Ritter, J. R., 1995. The new issues puzzle. Journal of Finance 50, 23–51.

Malmendier, U., Shanthikumar, D., 2007. Are small investors naive about incentives? Journal of Financial Economics 85, 457−489.

McLean, D., Pontiff, J., 2016. Does academic research destroy stock return predictability? Journal of Finance 71, 5−32.

McNichols, M., O'Brien, P., 1997. Self-selection and analyst coverage. Journal of Accounting Research 1997, 167–199.

Mikhail, M. B., Walther, B. R., Willis, R. H., 1997. Do security analysts improve their performance with experience? Journal of Accounting Research 35, 131–157.

Mikhail, M. B., Walther, B. R., Willis, R. H., 2007. When security analysts talk, who listens? The Accounting Review 82, 1227–1253.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, 277−309.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1–28.

O'Brien, P., McNichols, M. F., Lin, H. W., 2005. Analyst impartiality and investment banking relationships. Journal of Accounting Research 43, 623–650.

Ohlson, J. A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 18, 109–131.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435–480.

Pontiff, J., Woodgate, A., 2008. Share issuance and cross-sectional returns. Journal of Finance 63, 921–945.

Ritter, J. R., 1991. The long-run performance of initial public offerings. Journal of Finance 46, 3–27.

Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71, 289–315.

Stambaugh, R. F., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, 288–302.

Stambaugh, R. F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70, 1903–1948.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing factors. Review of Financial Studies 30, 1270–1315.

Stickel, S., 1991. Common stock returns surrounding earnings forecast revisions: More puzzling evidence. The Accounting Review 66, 402–16.

Titman, S., Wei, K. C. J., Xie, F., 2004. Capital investments and stock returns. Journal of Financial and Quantitative Analysis 39, 677–700.

Titman, S., Wei, K. C. J., Xie, F., 2013. Market development and the asset growth effect: International evidence. Journal of Financial and Quantitative Analysis 48, 1405–1432.

Weber, M., 2018. Cash flow duration and the term structure of equity returns. Journal of Financial Economics, forthcoming.

Womack, K. L., 1996. Do brokerage analysts' recommendations have investment value? Journal of Finance 51, 137–167.

Xing, Y., 2008. Interpreting the value effect through the q-theory: An empirical investigation. Review of Financial Studies 21, 1767–1795.

Yan, X., Zheng, L., 2017. Fundamental analysis and the cross-section of stock returns: A data-mining approach. Review of Financial Studies 30, 1382–1423.

Table 1: Summary statistics

This table reports the summary statistics for the sample, including the number of observations and the mean, median, standard deviation, and the 25th and 75th percentiles of the main variables used in the analysis. Rec (ΔRec) is the level (change) of analyst consensus recommendations, with recommendation coded as a number from 5 (strong buy) to 1 (strong sell). $Corr_{\text{MGMT}}$ ($Corr_{\text{PERF}}$) is the rank correlation between stocks' recommendation values and composite mispricing score MGMT (PERF), using all recommendations issued by each analyst over past three years. $|\Delta Rec_{individual}|$ is the absolute value of the change of individual analyst's recommendations. $AllStar$ is a dummy variable that equals one if the analyst is ranked as an All-American (first, second, third, or runner-up teams) in the Institutional Investor magazine and zero otherwise. $Concurrent\ Rec$ is a dummy variable that equals one if the analyst issues a forecast revision and also issues a recommendation change for the same stock in the three trading days surrounding the forecast revision date and the recommendation change is in the same direction as the forecast revision. $Pre\text{-}earnings$ ($Post\text{-}earnings$) is a dummy variable that equals one if the recommendation change is issued within two weeks prior to (after) an earnings announcement. $Away\ from\ consensus$ is a dummy variable that equals one if the absolute deviation of the recommendation change from the consensus is larger than the absolute deviation of the prior recommendation from the consensus. If a firm has fewer than three outstanding recommendations, this value is set to zero. $Accuracy$ is the difference between the absolute forecast error of analyst i on firm j's earnings and the average absolute forecast error across all analysts on firm *j*, scaled by the average absolute forecast error across all analysts' forecasts on firm *j*'s earnings. We then multiply this value by -1 and average across all stocks covered by an analyst in a given year, so that a higher value indicates that the analyst is on average more accurate. $Ln(FirmExp + 1)$ is the natural logarithm of one plus the number of days since the analyst first issued an earnings forecast on this firm. $Ln(TotalExp + 1)$ is the natural logarithm of one plus the number of days since the analyst first issued an earnings forecast for any firm. $Ln(BrokerSize)$ is the natural logarithm of the total number of analysts working at the brokerage firm. $Coverage$ is the total number of firms followed by an analyst in a given year. $Ln(Size)$ is the natural logarithm of firm market capitalization. $Average\ Size$ is defined as the average $Ln(Size)$ of stocks followed by an analyst in a given year. $Volatility$ is the standard deviation of daily returns over the 63 trading days prior to the recommendation change. $MOM_{(-21,-1)}$ is the cumulative stock returns over the 21 trading days prior to the recommendation change. $MOM_{(-252,-22)}$ is the cumulative stock returns over the 252 trading days prior to the recommendation change, excluding the 21 trading days prior to the recommendation changes. *Mutual Fund Net buys* is the change of stock ownership by mutual funds over the anomaly formation window (July of year *t* – 1 to June of year *t*).

Table 1 (continued): Summary statistics

Variable	N	Mean	Stdev	p25	p50	p75
Rec	708,907	3.85	0.60	3.43	3.89	4.25
ΔRec	690,679	0.04	0.68	-0.33	0.00	0.35
$Corr_{\text{MGMT}}$	562,391	-0.04	0.26	-0.19	-0.03	0.11
$Corr_{\text{PERF}}$	547,000	0.04	0.26	-0.11	0.04	0.19
$\lvert\Delta Rec_{individual}\rvert$	383,782	1.06	0.74	1.00	1.00	2.00
$AllStar$	574,954	0.09	0.29	0.00	0.00	0.00
$Concurrent\ Rec$	574,954	0.14	0.35	0.00	0.00	0.00
Pre-earnings	574,954	0.05	0.21	0.00	0.00	0.00
Post-earnings	574,954	0.07	0.26	0.00	0.00	0.00
$Away\ from\ consensus$	574,954	0.21	0.41	0.00	0.00	0.00
$Accuracy$	540,404	0.27	0.29	0.14	0.31	0.45
$Ln(FirmExp + 1)$	558,358	4.98	2.94	3.50	6.10	7.17
$Ln(TotalExp + 1)$	572,400	7.75	1.47	7.31	8.18	8.65
$Ln(BrokerSize)$	574,954	5.95	1.15	5.21	6.14	6.82
$Ln(Size)$	463,736	14.35	1.80	13.09	14.28	15.56
$MOM_{(-21,-1)}$	455,419	1.02%	15.87%	-6.94%	0.94%	8.45%
$MOM_{(-252,-22)}$	429,339	16.13%	55.67%	-15.29%	8.87%	35.15%
$Volatility$	446,408	3.04%	1.93%	1.76%	2.55%	3.73%
$Coverage$	574,954	9.57	6.54	5.00	8.00	13.00
$Average\ Size$	44,087	14.87	1.50	13.84	14.90	15.91
$Mutual\ Fund\ Net\ buys$	55,251	1.47%	5.63%	-1.20%	0.95%	3.94%

Table 2: Informativeness of anomaly signals

This table reports average monthly raw returns and alphas for the long-short portfolios of the 11 prominent anomalies and two composite mispricing measures. We classify the 11 anomalies into two clusters following Stambaugh and Yuan (2017). MGMT (PERF) stands for the composite mispricing measure of the first (second) cluster. Panel A (Panel B) reports the raw returns of Cluster 1 (Cluster 2) anomalies. Panel C (Panel D) reports the Fama-French three-factor alphas of Cluster 1 (Cluster 2) anomalies. The *t*-statistics in parentheses are based on Newey-West standard errors with optimal lag length. The sample period is from 1993 to 2014.

Panel A: Cluster 1 (Raw returns)							
	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Long	1.25%	1.23%	1.21%	1.14%	1.19%	1.26%	1.18%
	(3.80)	(3.94)	(4.29)	(2.82)	(3.34)	(3.18)	(3.09)
Short	0.53%	0.67%	0.76%	0.78%	0.57%	0.50%	0.59%
	(1.18)	(1.57)	(1.82)	(1.82)	(1.39)	(1.11)	(1.31)
Long – Short	0.72%	0.57%	0.44%	0.35%	0.62%	0.76%	0.60%
(*t*-stat)	(3.12)	(2.50)	(1.73)	(2.02)	(2.91)	(3.56)	(3.33)
Panel B: Cluster 2 (Raw returns)							
	PERF	Distress	O-score	MOM	GP	ROA	
Long	1.33%	1.29%	1.15%	1.28%	1.33%	1.33%	
	(3.82)	(4.15)	(3.41)	(3.15)	(3.73)	(3.67)	
Short	0.58%	0.81%	0.88%	0.62%	0.83%	0.51%	
	(1.30)	(2.11)	(1.97)	(1.34)	(2.36)	(0.93)	
Long – Short	0.75%	0.48%	0.27%	0.66%	0.50%	0.82%	
(*t*-stat)	(3.54)	(2.57)	(1.41)	(2.07)	(2.69)	(2.81)	
Panel C: Cluster 1 (Fama-French three-factor alphas)							
	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Long	0.23%	0.26%	0.32%	0.00%	0.17%	0.13%	0.07%
	(2.77)	(2.73)	(3.72)	(-0.01)	(1.61)	(1.20)	(0.72)
Short	-0.62%	-0.48%	-0.37%	-0.35%	-0.55%	-0.63%	-0.57%
	(-4.91)	(-4.87)	(-3.95)	(-3.28)	(-3.88)	(-5.09)	(-4.25)
Long – Short	0.86%	0.75%	0.68%	0.35%	0.72%	0.76%	0.64%
(*t*-stat)	(5.18)	(6.03)	(5.24)	(2.61)	(2.62)	(4.31)	(3.80)
Panel D: Cluster 2 (Fama-French three-factor alphas)							
	PERF	Distress	O-score	MOM	GP	ROA	
Long	0.36%	0.37%	0.13%	0.24%	0.29%	0.32%	
	(3.85)	(3.43)	(1.30)	(1.64)	(2.99)	(3.09)	
Short	-0.63%	-0.33%	-0.31%	-0.62%	-0.18%	-0.77%	
	(-4.56)	(-2.43)	(-2.49)	(-3.27)	(-1.24)	(-4.75)	
Long – Short	0.99%	0.69%	0.45%	0.86%	0.47%	1.09%	
(*t*-stat)	(5.63)	(3.95)	(2.94)	(2.95)	(2.13)	(4.69)	

Table 3: Analyst consensus recommendations for anomaly stocks

This table reports the average level (Column "Rec") and change (Column "ΔRec") of consensus recommendations for quintile portfolios sorted by the anomaly variables. We classify 11 anomalies into two clusters following Stambaugh and Yuan (2017). MGMT (PERF) stands for the composite mispricing measure of the first (second) cluster. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

Panel A: Cluster 1 (Recommendation level or change)

	MGMT		NSI		CEI		Accrual	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.52	-0.06	3.62	-0.09	3.54	-0.06	3.69	-0.06
2	3.63	-0.05	3.63	-0.05	3.60	-0.05	3.66	-0.05
3	3.76	-0.02	3.73	-0.03	3.76	-0.08	3.77	-0.01
4	3.90	-0.02	3.86	0.00	3.89	-0.03	3.89	0.00
Short	4.07	0.02	4.00	0.02	4.00	0.04	4.04	0.01
Long – Short	-0.55***	-0.08***	-0.38***	-0.10***	-0.46***	-0.10***	-0.35***	-0.06***
(*t*-stat)	(-13.47)	(-9.48)	(-11.31)	(-9.71)	(-10.70)	(-12.52)	(-9.05)	(-5.15)

	NOA		AG		IA	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.71	-0.04	3.61	-0.06	3.68	-0.01
2	3.70	-0.03	3.62	-0.04	3.74	-0.03
3	3.71	-0.02	3.74	-0.04	3.78	-0.03
4	3.77	-0.03	3.88	-0.02	3.86	-0.03
Short	4.00	-0.03	4.05	0.01	3.99	-0.02
Long – Short	-0.28***	-0.01	-0.44***	-0.06***	-0.32***	0.01
(*t*-stat)	(-12.04)	(-1.30)	(-10.02)	(-7.76)	(-7.62)	(0.66)

Panel B: Cluster 2 (Recommendation level or change)

	PERF		Distress		O-score		MOM	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.89	0.04	3.82	0.01	3.87	-0.02	3.89	0.07
2	3.83	0.01	3.83	0.01	3.80	0.01	3.76	0.00
3	3.77	-0.03	3.81	-0.01	3.77	-0.01	3.72	-0.01
4	3.69	-0.06	3.72	-0.03	3.75	-0.03	3.71	-0.06
Short	3.71	-0.11	3.64	-0.09	3.85	-0.05	3.77	-0.15
Long – Short	0.18***	0.15***	0.19***	0.10***	0.01	0.03**	0.12***	0.22***
(*t*-stat)	(5.62)	(5.58)	(9.03)	(3.86)	(0.36)	(2.35)	(4.36)	(7.33)

	GP		ROA	
	Rec	ΔRec	Rec	ΔRec
Long	3.83	-0.01	3.91	0.03
2	3.83	-0.02	3.83	0.01
3	3.83	-0.03	3.74	-0.03
4	3.73	-0.02	3.63	-0.07
Short	3.68	-0.06	3.81	-0.09
Long – Short	0.15***	0.05**	0.10**	0.12***
(*t*-stat)	(7.34)	(2.45)	(1.99)	(4.13)

Table 4: Abnormal returns of anomaly portfolios conditional on analyst recommendations

This table reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, stocks are sorted into three groups based on the level of analyst consensus recommendations and independently into quintiles based on each anomaly characteristic. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The sample period is from 1993 to 2014.

Panel A: Cluster 1 (Fama-French three-factor alphas)												
	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.40%	0.27%	0.17%	0.37%	0.32%	0.23%	0.44%	0.35%	0.27%	0.10%	-0.19%	0.07%
	(3.09)	(1.92)	(1.87)	(3.13)	(2.19)	(1.93)	(3.11)	(2.87)	(2.32)	(0.75)	(-1.20)	(0.57)
Short	-0.83%	-0.42%	-0.44%	-0.63%	-0.29%	-0.45%	-0.51%	-0.10%	-0.21%	-0.64%	-0.09%	-0.07%
	(-5.20)	(-3.31)	(-3.48)	(-4.94)	(-3.08)	(-3.98)	(-4.11)	(-1.07)	(-1.80)	(-4.65)	(-0.79)	(-0.65)
Consistent		0.85%			0.81%			0.65%			0.18%	
		(4.87)			(5.30)			(3.91)			(1.00)	
Inconsistent		1.00%			0.87%			0.77%			0.72%	
		(5.07)			(4.43)			(4.38)			(3.80)	
Diff: Incon – Con		0.16%			0.05%			0.12%			0.54%	
		(0.85)			(0.29)			(0.65)			(2.34)	
	NOA			AG			IA					
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down			
Long	0.08%	0.30%	0.18%	0.22%	0.18%	0.06%	0.11%	0.02%	0.14%			
	(0.50)	(2.50)	(1.37)	(1.45)	(1.23)	(0.67)	(0.93)	(0.13)	(1.31)			
Short	-0.69%	-0.44%	-0.48%	-0.84%	-0.41%	-0.44%	-0.85%	-0.44%	-0.38%			
	(-4.21)	(-3.07)	(-3.39)	(-5.25)	(-3.53)	(-3.04)	(-5.00)	(-2.86)	(-2.21)			
Consistent		0.56%			0.66%			0.48%				
		(1.53)			(3.40)			(2.93)				
Inconsistent		0.87%			0.90%			0.99%				
		(3.21)			(4.09)			(4.54)				
Diff: Incon – Con		0.31%			0.24%			0.51%				
		(1.56)			(1.22)			(2.41)				

Table 4 (continued): Abnormal returns of anomaly portfolios conditional on analyst recommendations

Panel B: Cluster 2 (Fama-French three-factor alphas)												
	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.40%	0.39%	0.47%	0.36%	0.21%	0.36%	0.08%	0.15%	0.22%	0.40%	0.54%	0.41%
	(3.48)	(3.96)	(4.11)	(2.69)	(1.58)	(3.24)	(0.72)	(1.30)	(2.01)	(2.65)	(2.75)	(2.94)
Short	-1.09%	-0.54%	-0.50%	-0.71%	-0.08%	-0.27%	-0.55%	-0.22%	-0.18%	-1.09%	-0.68%	-0.45%
	(-5.87)	(-3.42)	(-4.13)	(-4.26)	(-0.46)	(-1.84)	(-3.08)	(-1.50)	(-1.23)	(-4.87)	(-2.88)	(-2.14)
Consistent		0.90%			0.63%			0.26%			0.85%	
		(5.21)			(2.98)			(1.54)			(2.75)	
Inconsistent		1.57%			1.07%			0.76%			1.50%	
		(6.47)			(5.34)			(3.72)			(4.44)	
Diff: Incon – Con		0.67%			0.44%			0.50%			0.65%	
		(2.96)			(1.96)			(2.31)			(3.29)	
	GP			ROA								
	Up	Middle	Down	Up	Middle	Down						
Long	0.22%	0.34%	0.37%	0.28%	0.42%	0.49%						
	(2.10)	(2.94)	(2.69)	(2.30)	(3.72)	(3.23)						
Short	-0.39%	-0.04%	-0.11%	-1.07%	-0.70%	-0.63%						
	(-2.26)	(-0.28)	(-0.65)	(-5.79)	(-3.82)	(-4.31)						
Consistent		0.33%			0.91%							
		(1.86)			(4.34)							
Inconsistent		0.76%			1.56%							
		(2.78)			(6.65)							
Diff: Incon – Con		0.43%			0.65%							
		(2.27)			(3.06)							

Table 5: Fama-MacBeth regressions

This table reports the Fama and MacBeth (1973) regressions of stock returns (in percentage) on anomaly characteristics interacted with analyst consensus recommendations. Long (short) is a dummy variable that equals one for stocks in the most undervalued (overvalued) quintile based on anomaly characteristics and zero otherwise. RecUp (RecMid, RecDown) is a dummy variable that equals one for stocks in the top (middle, bottom) tercile based on analyst consensus recommendations and zero otherwise. We run the Fama-MacBeth regression of the form:

$$Ret_{i,t+1} = \alpha + \beta_1 Long \times RecUp + \beta_2 Long \times RecMid + \beta_3 Long \times RecDown + \beta_4 Short \times RecUp + \beta_5 Short \times RecMid + \beta_6 Short \times RecDown + \beta_7 Missing + \sum \beta_k X_{k,i,t} + \epsilon_{i,t+1},$$

where $X_{k,i,t}$ stands for a set of control variables, including firm size (Ln(Size)), short-term reversal (Rev), book-to-market ratio (Ln(BM)), idiosyncratic volatility (IVOL), past 12-month average turnover (Turnover), analyst forecast dispersion (Disp), and maximum daily return (MaxReturn). We replace the missing value of a control variable with its cross-sectional monthly median value and add a dummy variable $Missing$ that equals one when there is at least one missing value for any of the control variables and zero otherwise. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The t-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

Panel A: Cluster 1

	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Long×RecUp	0.127	0.024	0.144	0.151	-0.055	0.308**	0.015
	(1.02)	(0.22)	(0.99)	(1.17)	(-0.32)	(2.34)	(0.15)
Long×RecMid	0.191	0.023	0.093	0.013	0.133	0.267	0.005
	(1.52)	(0.17)	(0.79)	(0.11)	(0.84)	(1.62)	(0.04)
Long×RecDown	0.033	0.029	-0.120	0.257*	-0.046	0.177	0.231*
	(0.34)	(0.26)	(-1.04)	(1.94)	(-0.28)	(1.37)	(1.93)
Short×RecUp	-0.810***	-0.645***	-0.330**	-0.570***	-0.660***	-0.753***	-0.755***
	(-6.19)	(-4.84)	(-2.32)	(-3.76)	(-4.97)	(-4.50)	(-4.54)
Short×RecMid	-0.337**	-0.226	0.089	-0.027	-0.520***	-0.318*	-0.186
	(-2.19)	(-1.36)	(0.79)	(-0.12)	(-3.68)	(-1.85)	(-1.01)
Short×RecDown	-0.579***	-0.474***	-0.326**	-0.269*	-0.541***	-0.492***	-0.462**
	(-3.68)	(-3.28)	(-2.07)	(-1.71)	(-3.97)	(-2.92)	(-2.56)
Rev	-1.294**	-1.291**	-2.182***	-1.293**	-1.395**	-1.261**	-1.276**
	(-2.13)	(-2.10)	(-3.32)	(-2.14)	(-2.28)	(-2.04)	(-2.14)
Ln(Size)	-0.072	-0.056	-0.029	-0.086	-0.074	-0.073	-0.088*
	(-1.46)	(-1.14)	(-0.57)	(-1.51)	(-1.52)	(-1.50)	(-1.68)
Ln(BM)	0.041	0.032	-0.025	0.033	0.064	0.029	0.046
	(0.42)	(0.33)	(-0.24)	(0.34)	(0.66)	(0.30)	(0.47)
IVOL	-12.811**	-12.376**	-18.837***	-14.446***	-13.737**	-13.106**	-14.192***
	(-2.44)	(-2.39)	(-3.38)	(-2.66)	(-2.53)	(-2.52)	(-2.70)
Turnover	0.573	0.301	0.196	-0.038	0.493	0.418	0.257
	(0.69)	(0.35)	(0.21)	(-0.05)	(0.59)	(0.51)	(0.33)
Disp	-0.004	-0.293	-0.193	0.098	0.039	0.001	0.045
	(-0.04)	(-1.22)	(-0.49)	(0.76)	(0.40)	(0.01)	(0.47)
MaxReturn	-1.131	-0.929	-1.647	-0.550	-0.879	-1.188	-0.801
	(-0.81)	(-0.69)	(-1.08)	(-0.39)	(-0.60)	(-0.86)	(-0.55)
Missing	0.160*	0.262***	0.382***	0.341***	0.191**	0.186**	0.241**
	(1.71)	(2.67)	(3.25)	(2.83)	(1.97)	(2.06)	(2.35)
Intercept	2.459***	2.247***	1.903**	2.590***	2.487***	2.395***	2.680***
	(3.10)	(2.89)	(2.37)	(2.84)	(3.10)	(3.06)	(3.15)
Observations	668,865	650,129	605,441	513,929	667,793	669,836	575,196
Adjusted R^2	0.063	0.065	0.072	0.063	0.066	0.065	0.062

Table 5 (continued): Fama-MacBeth regressions

Panel B: Cluster 2						
	PERF	Distress	O-score	MOM	GP	ROA
Long×RecUp	0.319***	0.285*	-0.003	0.413**	0.281**	0.482***
	(2.78)	(1.92)	(-0.02)	(2.24)	(2.24)	(3.80)
Long×RecMid	0.365**	0.056	0.111	0.503**	0.499**	0.602***
	(2.40)	(0.37)	(0.76)	(2.53)	(2.56)	(3.54)
Long×RecDown	0.300**	0.361*	0.189	0.527**	0.487***	0.591***
	(2.18)	(1.95)	(1.59)	(2.33)	(3.28)	(3.85)
Short×RecUp	-1.041***	-0.798***	-0.474**	-0.701***	-0.537***	-0.800***
	(-4.67)	(-3.49)	(-2.57)	(-2.88)	(-2.63)	(-2.85)
Short×RecMid	-0.336**	0.062	-0.146	0.087	-0.157	-0.270
	(-1.99)	(0.32)	(-0.80)	(0.33)	(-0.74)	(-1.02)
Short×RecDown	-0.547***	-0.537***	0.032	-0.091	-0.402*	-0.268
	(-3.53)	(-3.16)	(0.21)	(-0.37)	(-1.87)	(-1.19)
Rev	-1.390**	-2.990***	-1.235**	-1.548**	-1.239**	-1.257**
	(-2.34)	(-4.41)	(-2.03)	(-2.44)	(-2.09)	(-2.04)
Ln(Size)	-0.098*	-0.055	-0.103*	-0.042	-0.074	-0.081
	(-1.92)	(-1.01)	(-1.83)	(-0.81)	(-1.53)	(-1.61)
Ln(BM)	0.114	0.159	0.045	0.036	0.129	0.116
	(1.18)	(1.31)	(0.50)	(0.37)	(1.26)	(1.31)
IVOL	-13.172**	-12.398*	-13.776**	-16.137***	-15.576***	-14.979***
	(-2.42)	(-1.69)	(-2.55)	(-2.91)	(-2.92)	(-3.09)
Turnover	-0.126	-1.094	-0.045	-0.511	0.117	0.137
	(-0.15)	(-0.87)	(-0.05)	(-0.62)	(0.14)	(0.18)
Disp	0.202**	-1.108	0.100	0.241	0.049	0.133
	(1.97)	(-1.32)	(0.87)	(1.24)	(0.46)	(1.55)
MaxReturn	-0.570	-0.123	-0.396	-1.578	-1.488	-1.011
	(-0.42)	(-0.07)	(-0.27)	(-1.15)	(-1.04)	(-0.75)
Missing	0.242**	0.185	0.366***	0.259***	0.180*	0.158
	(2.59)	(0.35)	(3.37)	(2.74)	(1.88)	(1.64)
Intercept	2.791***	2.247**	2.768***	2.059***	2.568***	2.554***
	(3.49)	(2.56)	(3.04)	(2.61)	(3.27)	(3.14)
Observations	661,412	359,496	522,326	616,331	673,591	691,037
Adjusted R^2	0.068	0.075	0.064	0.079	0.069	0.067

Table 6: Mutual fund net buys in anomaly portfolios conditional on analyst recommendations

This table reports the change of stock ownership by mutual funds (mutual fund net buys) over the portfolio formation window (July of year *t*-1 to June of year *t*). At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations and independently into quintiles based on anomaly characteristics. We calculate the average mutual fund net buys for each portfolio over the portfolio formation window. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Long×RecUp – Long×RecDown (Short×RecUp – Short×RecDown) reports the difference in mutual fund net buys between stocks with the most favorable and most unfavorable consensus recommendations for the long-leg portfolio (short-leg portfolio). Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The Newey-West adjusted *t*-statistics are shown in parentheses. The sample period is from 1993 to 2014.

Panel A: Cluster 1 (Mutual fund net buys)

	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	1.00%	0.69%	0.47%	1.40%	0.73%	0.42%	1.31%	0.77%	0.64%	2.06%	1.24%	0.43%
	(5.06)	(5.32)	(2.86)	(5.70)	(4.67)	(2.61)	(6.92)	(14.97)	(4.60)	(11.36)	(6.31)	(1.96)
Short	3.86%	2.65%	0.91%	4.30%	2.77%	1.12%	4.27%	2.95%	1.42%	3.62%	2.20%	0.62%
	(14.04)	(13.80)	(2.93)	(20.3)	(16.76)	(3.90)	(16.46)	(13.06)	(6.56)	(14.63)	(11.42)	(1.45)
Long×RecUp – Long×RecDown		0.53%			0.98%			0.67%			1.63%	
		(2.65)			(6.00)			(3.97)			(7.65)	
Short×RecUp – Short×RecDown		2.95%			3.18%			2.84%			3.01%	
		(7.16)			(8.41)			(7.43)			(5.15)	

	NOA			AG			IA		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	2.59%	1.52%	0.56%	1.50%	1.06%	0.32%	2.13%	1.32%	0.52%
	(15.69)	(13.27)	(2.52)	(9.34)	(6.05)	(1.80)	(11.48)	(6.72)	(2.53)
Short	2.93%	1.65%	0.30%	4.00%	2.55%	0.95%	3.21%	1.87%	0.52%
	(9.60)	(8.20)	(1.14)	(17.02)	(13.44)	(3.15)	(12.59)	(8.67)	(1.63)
Long×RecUp – Long×RecDown		2.03%			1.18%			1.61%	
		(13.08)			(6.17)			(11.19)	
Short×RecUp – Short×RecDown		2.63%			3.05%			2.69%	
		(7.95)			(8.01)			(5.94)	

Table 6 (continued): Mutual fund net buys in anomaly portfolios conditional on analyst recommendations

Panel B: Cluster 2 (Mutual fund net buys)

	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	2.95%	1.59%	0.95%	2.35%	1.21%	0.84%	3.12%	1.53%	0.72%	3.22%	2.15%	0.94%
	(10.52)	(7.90)	(5.35)	(8.16)	(5.43)	(4.14)	(12.39)	(7.02)	(2.28)	(12.43)	(8.94)	(5.62)
Short	2.23%	1.36%	0.32%	1.92%	1.47%	0.64%	2.41%	1.59%	-0.31%	2.46%	1.27%	0.39%
	(12.19)	(8.16)	(1.83)	(11.59)	(5.51)	(2.19)	(11.21)	(6.16)	(-1.80)	(21.51)	(6.65)	(1.30)
Long×RecUp – Long×RecDown		2.00%			1.52%			2.40%			2.28%	
		(8.13)			(8.50)			(5.26)			(11.58)	
Short×RecUp – Short×RecDown		1.91%			1.28%			2.71%			2.07%	
		(9.13)			(4.14)			(13.54)			(8.64)	

	GP			ROA		
	Up	Middle	Down	Up	Middle	Down
Long	2.77%	1.43%	0.64%	2.99%	1.57%	0.82%
	(12.81)	(10.57)	(2.61)	(11.07)	(7.27)	(4.73)
Short	2.16%	1.38%	0.61%	2.56%	1.45%	0.17%
	(13.44)	(13.03)	(3.42)	(16.88)	(6.82)	(0.79)
Long×RecUp – Long×RecDown		2.12%			2.17%	
		(8.17)			(8.71)	
Short×RecUp – Short×RecDown		1.55%			2.39%	
		(9.97)			(11.52)	

Table 7: Price run-up of anomaly portfolios conditional on analyst recommendations one quarter ago

This table reports the buy-and-hold cumulative abnormal returns (CARs) of anomaly portfolios over the period from April to June of year *t*. We sort stocks into three groups based on the level of analyst consensus recommendations available at the end of March of year *t* and independently into quintiles based on anomaly characteristics at the end of June of year *t*. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. The CAR is calculated as the individual stock buy-and-hold cumulative return minus the cumulative value-weighted market index return, and then averaged to the portfolio level. Long×RecUp – Long×RecDown (Short×RecUp – Short×RecDown) reports the difference in CARs between stocks with the most favorable and most unfavorable consensus recommendations for the long-leg portfolio (short-leg portfolio). Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The Newey-West adjusted *t*-statistics are shown in parentheses. The sample period is from 1993 to 2014.

Panel A: Cluster 1

	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	3.74%	2.07%	-1.09%	3.18%	0.70%	-1.43%	4.10%	1.98%	0.95%	4.52%	0.94%	-3.37%
	(2.56)	(2.56)	(-1.34)	(2.44)	(0.78)	(-1.39)	(4.26)	(2.20)	(1.14)	(2.27)	(1.40)	(-3.59)
Short	7.91%	4.43%	0.14%	8.93%	5.21%	-0.12%	8.91%	6.69%	2.73%	9.82%	5.25%	0.14%
	(4.53)	(3.65)	(0.12)	(4.58)	(13.56)	(-0.22)	(4.67)	(6.12)	(3.18)	(4.74)	(3.69)	(0.10)
Long×RecUp – Long×RecDown		4.83%			4.61%			3.15%			7.89%	
		(4.96)			(4.22)			(5.98)			(4.11)	
Short×RecUp – Short×RecDown		7.77%			9.05%			6.19%			9.68%	
		(5.64)			(5.84)			(4.69)			(4.46)	

	NOA			AG			IA		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	6.68%	3.53%	0.60%	4.34%	1.02%	-2.30%	6.40%	3.12%	-0.94%
	(3.50)	(3.45)	(0.60)	(2.66)	(1.69)	(-5.56)	(3.73)	(4.74)	(-2.48)
Short	5.61%	1.18%	-2.75%	8.91%	4.89%	0.74%	6.55%	1.37%	-2.17%
	(5.14)	(2.27)	(-2.58)	(4.76)	(3.95)	(0.46)	(3.38)	(1.19)	(-1.96)
Long×RecUp – Long×RecDown		6.08%			6.64%			7.35%	
		(4.40)			(6.07)			(5.91)	
Short×RecUp – Short×RecDown		8.36%			8.17%			8.72%	
		(7.17)			(5.42)			(5.15)	

Table 7 (continued): Price run-up of anomaly portfolios conditional on analyst recommendations one quarter ago

Panel B: Cluster 2

	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	9.83%	5.40%	3.45%	4.01%	1.09%	-0.66%	6.99%	2.97%	-0.39%	14.39%	11.41%	9.65%
	(7.23)	(5.40)	(4.05)	(3.46)	(1.21)	(-0.76)	(4.66)	(2.36)	(-0.42)	(7.55)	(8.34)	(8.19)
Short	2.47%	-1.32%	-4.12%	4.27%	1.85%	-1.02%	6.46%	2.50%	-3.21%	-0.83%	-5.28%	-8.63%
	(1.83)	(-1.53)	(-6.46)	(2.39)	(1.28)	(-0.98)	(3.53)	(2.35)	(-2.63)	(-0.43)	(-7.94)	(-13.31)
Long×RecUp – Long×RecDown		6.38%			4.67%			7.38%			4.74%	
		(4.83)			(6.40)			(5.35)			(2.92)	
Short×RecUp – Short×RecDown		6.59%			5.29%			9.67%			7.80%	
		(4.70)			(3.46)			(5.44)			(5.45)	

	GP			ROA		
	Up	Middle	Down	Up	Middle	Down
Long	7.51%	2.55%	-2.27%	9.08%	4.50%	2.22%
	(4.53)	(2.45)	(-2.17)	(5.64)	(4.27)	(2.71)
Short	5.14%	2.60%	1.16%	5.65%	1.56%	-4.11%
	(2.53)	(2.25)	(1.00)	(5.81)	(3.66)	(-18.80)
Long×RecUp – Long×RecDown		9.78%			6.86%	
		(6.72)			(5.82)	
Short×RecUp – Short×RecDown		3.98%			9.77%	
		(3.78)			(6.95)	

Table 8: Determinants of analyst skills

This table reports the panel regression results of our measure of analyst skill on a set of analyst and firm characteristics. We conduct the panel regression of the form:

$$Corr_{s,i,t} = \alpha + \beta_1 AllStar + \beta_2 Away\ from\ consensus + \beta_3 Accuracy + \beta_4 Ln(FirmExp + 1) + \beta_5 Ln(TotalExp + 1) + \beta_6 Ln(BrokerSize) + \beta_7 Coverage + \beta_8 Average\ Size + \epsilon_{i,t}.$$

The dependent variable $Corr_{s,i,t}$ is the rank correlation between stocks' recommendations and two composite mispricing scores, MGMT or PERF, using all recommendations issued by each analyst *i* over the last three years up to year *t*. All other variables are defined in Table 1. Standard errors are double clustered by analyst and year and *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	$Corr_{MGMT}$				$Corr_{PERF}$			
$AllStar$	-0.004	-0.013**	-0.003	-0.010*	0.008	0.013**	0.007	0.012**
	(-0.65)	(-2.06)	(-0.49)	(-1.68)	(1.43)	(2.02)	(1.31)	(1.97)
$Away\ from\ consensus$	-0.001	0.000	-0.001	-0.000	-0.001	-0.003	-0.001	-0.003
	(-0.26)	(0.07)	(-0.36)	(-0.13)	(-0.27)	(-1.01)	(-0.18)	(-0.94)
$Accuracy$	0.011*	0.003	0.011*	0.004	0.014**	0.006	0.013**	0.004
	(1.79)	(0.49)	(1.95)	(0.65)	(2.31)	(1.02)	(2.04)	(0.68)
$Ln(FirmExp + 1)$	-0.000	-0.001	-0.000	-0.001	-0.001	-0.001	-0.000	-0.001
	(-0.57)	(-1.11)	(-0.67)	(-1.29)	(-1.02)	(-1.55)	(-0.62)	(-1.11)
$Ln(TotalExp + 1)$	-0.006***	-0.006**	-0.006***	-0.007***	0.004*	-0.001	0.004**	0.003
	(-3.16)	(-2.44)	(-3.32)	(-2.84)	(1.94)	(-0.34)	(2.20)	(0.99)
$Ln(BrokerSize)$	-0.008***	-0.007***	-0.008***	-0.007***	0.005***	0.002	0.004***	0.002
	(-5.27)	(-3.89)	(-5.31)	(-3.64)	(3.17)	(1.37)	(2.75)	(1.27)
$Coverage$	-0.000	-0.000**	-0.000	-0.000**	0.000	0.000*	0.000	0.000
	(-0.65)	(-2.25)	(-0.55)	(-2.28)	(1.55)	(1.80)	(0.89)	(1.50)
$Average\ Size$	0.003***	0.003*	0.003**	0.001	-0.002	-0.002	0.000	-0.000
	(2.79)	(1.86)	(2.24)	(0.82)	(-1.28)	(-1.10)	(0.15)	(-0.02)
Intercept	0.018	0.023	0.027	0.015	0.004	0.051*	-0.020	0.037
	(0.86)	(0.89)	(1.28)	(0.53)	(0.18)	(1.92)	(-0.89)	(1.29)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Analyst FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	34,866	34,866	34,866	34,866	33,705	33,705	33,705	33,705
Adjusted R^2	0.002	0.002	0.002	0.004	0.001	0.001	0.001	0.005

Table 9: Market reactions to skilled analysts' recommendation changes

This table reports the panel regression results of analyst recommendation announcement returns on our measure of analyst skill. We estimate the panel regression of the form:

$$CAR[0,+1]) = \alpha + \beta_1 Corr_s + \beta_2 |\Delta Rec_{individual}| + \beta_3 AllStar + \beta_4 Concurrent\ Rec$$
$$+\beta_5 Pre\text{-}earnings + \beta_6 Post\text{-}earnings + \beta_7 Away\ from\ consensus + \beta_8 Accuracy$$
$$+\beta_9 Ln(FirmExp + 1) + \beta_{10} Ln(TotalExp + 1) + \beta_{11} Ln(BrokerSize) + \beta_{12} Coverage$$
$$+\sum \beta_k X_{k,i,t} + \epsilon_{i,t}.$$

The dependent variable ($CAR[0,+1]$) is the 2-day cumulative abnormal returns (in percentage) around recommendation change announcements. $Corr_s$ is the rank correlation between stocks' recommendations and two composite mispricing scores, MGMT or PERF, using all recommendations issued by each analyst over the last three years. All other variables are defined in Table 1. $X_{k,i,t}$ represents the vector of firm characteristics, including $Ln(Size)$, $Volatility$, $MOM_{(-21,-1)}$, and $MOM_{(-252,-22)}$. Panel A (Panel B) reports the results for upgrade (downgrade) recommendation changes. Standard errors are double clustered by firm and analyst and *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Upgrade recommendation changes ($CAR[0,+1]$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	-0.000	0.000	-0.001			
	(-0.43)	(0.39)	(-0.53)			
$Corr_{PERF}$				0.002**	0.003**	0.004*
				(2.26)	(2.21)	(1.86)
$\|\Delta Rec_{individual}\|$	0.003***	0.005***	0.005***	0.003***	0.005***	0.005***
	(7.74)	(8.71)	(6.84)	(7.85)	(8.94)	(6.92)
$AllStar$	0.006***	0.002**	0.001	0.006***	0.003**	0.002
	(8.77)	(2.28)	(0.94)	(8.83)	(2.42)	(1.36)
$Concurrent\ Rec$	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(30.73)	(28.33)	(19.87)	(30.48)	(28.05)	(19.28)
$Pre\text{-}earnings$	0.005***	0.003***	0.004**	0.004***	0.003***	0.004**
	(4.60)	(3.33)	(2.42)	(4.24)	(2.99)	(2.46)
$Post\text{-}earnings$	0.002**	0.002***	0.002	0.002***	0.002***	0.002*
	(2.45)	(2.79)	(1.47)	(2.65)	(3.14)	(1.69)
$Away\ from\ consensus$	0.002***	0.001***	0.002***	0.002***	0.001**	0.002***
	(4.06)	(2.96)	(3.06)	(3.80)	(2.45)	(2.99)
$Accuracy$	0.006***	0.002	0.001	0.006***	0.002	0.000
	(7.21)	(1.61)	(0.65)	(6.84)	(1.41)	(0.33)
$Ln(FirmExp + 1)$	0.000	0.000	-0.000	0.000	0.000	-0.000
	(1.29)	(0.85)	(-0.63)	(1.14)	(0.47)	(-0.38)
$Ln(TotalExp + 1)$	0.001***	0.001	0.002	0.001***	0.001	0.003*
	(5.21)	(1.36)	(1.49)	(5.37)	(1.52)	(1.92)
$Ln(BrokerSize)$	0.003***	0.002***	0.002***	0.003***	0.002***	0.002***
	(16.07)	(4.47)	(3.10)	(15.80)	(4.36)	(2.73)
$Coverage$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-7.10)	(-9.23)	(-4.37)	(-6.70)	(-8.74)	(-4.28)
Intercept	-0.033***	-0.040***	-0.002	-0.031***	-0.038***	-0.002
	(-3.29)	(-3.65)	(-0.08)	(-3.07)	(-3.48)	(-0.08)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	Yes	No	Yes
Analyst FE	No	Yes	Yes	No	Yes	Yes
Observations	94,046	94,046	94,046	91,545	91,545	91,545
Adjusted R^2	0.074	0.080	0.069	0.071	0.076	0.064

Table 9 (continued): Market reactions to skilled analysts' recommendation changes

Panel B: Downgrade recommendation changes ($CAR[0, +1]$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	-0.003**	-0.004*	-0.005*			
	(-2.13)	(-1.90)	(-1.76)			
$Corr_{PERF}$				-0.005***	-0.006***	-0.007***
				(-3.34)	(-3.06)	(-2.71)
$\|\Delta Rec_{individual}\|$	-0.008***	-0.013***	-0.014***	-0.009***	-0.013***	-0.015***
	(-11.88)	(-13.50)	(-10.30)	(-11.94)	(-13.32)	(-10.38)
$AllStar$	-0.009***	-0.004**	-0.002	-0.008***	-0.004**	-0.001
	(-8.18)	(-2.57)	(-0.80)	(-7.95)	(-2.41)	(-0.64)
$Concurrent\ Rec$	-0.038***	-0.038***	-0.034***	-0.039***	-0.039***	-0.035***
	(-44.88)	(-41.57)	(-27.21)	(-45.10)	(-41.79)	(-27.50)
$Pre\text{-}earnings$	-0.004***	-0.005***	-0.002	-0.004***	-0.005***	-0.002
	(-2.83)	(-2.93)	(-0.98)	(-3.13)	(-3.15)	(-1.04)
$Post\text{-}earnings$	-0.012***	-0.013***	-0.010***	-0.012***	-0.013***	-0.010***
	(-10.69)	(-10.74)	(-6.16)	(-10.74)	(-10.79)	(-5.85)
$Away\ from\ consensus$	-0.000	-0.002**	-0.001	-0.000	-0.001*	-0.001
	(-0.69)	(-2.09)	(-0.79)	(-0.56)	(-1.77)	(-0.72)
$Accuracy$	-0.008***	-0.003**	-0.001	-0.008***	-0.004**	-0.002
	(-6.69)	(-2.23)	(-0.67)	(-6.90)	(-2.40)	(-0.91)
$Ln(FirmExp + 1)$	0.000	0.001***	0.001	0.000	0.001***	0.001
	(0.76)	(3.88)	(1.40)	(0.82)	(3.60)	(0.94)
$Ln(TotalExp + 1)$	-0.001***	-0.003*	0.000	-0.001***	-0.002	0.001
	(-3.58)	(-1.86)	(0.22)	(-3.50)	(-1.63)	(0.40)
$Ln(BrokerSize)$	-0.005***	-0.002***	-0.000	-0.005***	-0.002***	-0.000
	(-16.91)	(-3.44)	(-0.50)	(-16.65)	(-3.15)	(-0.10)
$Coverage$	-0.002***	-0.001***	-0.002***	-0.002***	-0.001***	-0.002***
	(-16.08)	(-6.35)	(-9.96)	(-15.39)	(-6.13)	(-9.73)
Intercept	0.019	0.028*	-0.061**	0.029**	0.029*	-0.060**
	(1.37)	(1.78)	(-2.20)	(1.99)	(1.77)	(-2.13)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	Yes	No	Yes
Analyst FE	No	Yes	Yes	No	Yes	Yes
Observations	114,003	114,003	114,003	111,237	111,237	111,237
Adjusted R^2	0.079	0.101	0.079	0.080	0.102	0.078

Table 10: Subsample tests in post-publication periods

This table reports the results in post-publication periods. Panel A reports the Fama-French three-factor alphas of long-short portfolios sorted by 11 anomalies. Panel B reports the average level and change of analyst consensus recommendations across quintile portfolios of 11 anomalies. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fama-French three-factor alphas						
	NSI	CEI	Accrual	NOA	AG	IA
Long	0.26%	0.10%	0.03%	-0.08%	0.16%	-0.01%
	(2.73)	(0.85)	(0.24)	(-0.50)	(1.42)	(-0.09)
Short	-0.49%	-0.27%	-0.33%	-0.22%	-0.20%	-0.30%
	(-4.87)	(-2.75)	(-2.81)	(-2.77)	(-1.46)	(-2.46)
Long – Short	0.75%	0.37%	0.36%	0.14%	0.36%	0.29%
(*t*-stat)	(6.03)	(2.58)	(2.45)	(0.61)	(1.73)	(1.70)
	Distress	O-score	MOM	GP	ROA	
Long	0.09%	-0.03%	0.24%	0.16%	-0.02%	
	(0.92)	(-0.31)	(1.64)	(1.10)	(-0.25)	
Short	0.20%	0.16%	-0.62%	0.60%	-0.38%	
	(1.49)	(1.49)	(-3.27)	(6.35)	(-2.27)	
Long – Short	-0.11%	-0.20%	0.86%	-0.44%	0.35%	
(*t*-stat)	(-0.56)	(-1.00)	(2.95)	(-2.06)	(1.96)	

Table 10 (continued): Subsample tests in post-publication periods

Panel B: Recommendation level or change

	NSI		CEI		Accrual		NOA	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.62	-0.09	3.49	-0.05	3.69	-0.06	3.60	0.01
2	3.63	-0.05	3.51	-0.02	3.67	-0.05	3.59	0.00
3	3.73	-0.03	3.64	-0.02	3.77	-0.01	3.64	0.01
4	3.86	0.00	3.76	0.00	3.88	0.01	3.65	0.00
Short	4.00	0.02	3.84	0.04	4.03	0.01	3.84	0.01
Long – Short	-0.38***	-0.10***	-0.36***	-0.09***	-0.34***	-0.06***	-0.24***	-0.00
(*t*-stat)	(-12.65)	(-9.71)	(-13.95)	(-8.52)	(-10.71)	(-4.93)	(-13.69)	(-0.08)

	AG		IA	
	Rec	ΔRec	Rec	ΔRec
Long	3.58	-0.03	3.60	0.02
2	3.58	0.01	3.67	-0.01
3	3.63	0.00	3.68	0.01
4	3.74	0.02	3.72	0.01
Short	3.91	0.03	3.83	0.01
Long – Short	-0.33***	-0.06***	-0.23***	0.02
(*t*-stat)	(-25.93)	(-9.69)	(-13.31)	(0.91)

	Distress		O-score		MOM		GP	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.70	0.01	3.72	0.00	3.89	0.07	3.72	-0.01
2	3.73	0.01	3.72	0.03	3.76	0.00	3.79	-0.02
3	3.73	0.02	3.70	0.00	3.72	-0.01	3.78	0.01
4	3.65	0.02	3.72	-0.01	3.71	-0.06	3.69	0.00
Short	3.54	-0.02	3.82	-0.01	3.77	-0.15	3.63	0.00
Long – Short	0.16***	0.03***	-0.10**	0.01	0.12***	0.22***	0.09***	-0.01
(*t*-stat)	(5.11)	(2.98)	(-2.60)	(0.53)	(4.36)	(8.24)	(3.17)	(-0.74)

	ROA	
	Rec	ΔRec
Long	3.72	0.02
2	3.72	0.03
3	3.64	0.00
4	3.54	-0.01
Short	3.74	-0.03
Long – Short	-0.02	0.05***
(*t*-stat)	(-0.35)	(3.57)

Table 11: Subsample tests based on firm size

This table reports the results for subsamples based on firm size. We define small (big) stocks as those with market capitalization below (above) the 30% size cutoff using the NYSE size breakpoints. Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing scores, MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, all stocks are sorted into three groups based on the level of analyst consensus recommendations and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	Small Stocks				Big Stocks			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.60	-0.07	4.04	0.07	3.46	-0.06	3.81	0.03
2	3.70	-0.07	3.93	-0.02	3.57	-0.03	3.75	0.01
3	3.85	-0.04	3.81	-0.06	3.68	-0.01	3.70	0.00
4	3.97	-0.04	3.72	-0.09	3.82	0.00	3.63	-0.03
Short	4.14	-0.01	3.76	-0.13	3.99	0.04	3.62	-0.08
Long – Short	-0.54***	-0.07***	0.28***	0.20***	-0.53***	-0.10***	0.19***	0.11***
(*t*-stat)	(-24.79)	(-4.37)	(9.11)	(7.54)	(-12.04)	(-10.24)	(6.56)	(4.20)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.52%	0.24%	0.61%	0.67%	0.17%	0.08%	0.26%	0.41%
	(2.98)	(2.04)	(4.36)	(5.10)	(1.54)	(0.81)	(2.18)	(3.19)
Short	-0.86%	-0.51%	-1.29%	-0.61%	-0.71%	-0.31%	-0.82%	-0.36%
	(-4.95)	(-2.57)	(-5.99)	(-3.66)	(-3.84)	(-2.00)	(-3.77)	(-3.45)
Consistent	1.03%		1.22%		0.48%		0.63%	
	(3.23)		(6.21)		(2.49)		(3.47)	
Inconsistent	1.10%		1.96%		0.80%		1.23%	
	(5.14)		(7.56)		(3.67)		(4.04)	
Diff: Incon – Con	0.07%		0.74%		0.32%		0.60%	
	(0.33)		(2.96)		(1.15)		(2.21)	

Table 12: Subsample tests based on institutional ownership

This table reports the results for subsamples based on institutional ownership. We divide stocks into high and low institutional ownership groups according to the median institutional ownership each quarter. Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing measures MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, all stocks are sorted into three groups based on the level of analyst consensus recommendations and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	Low Institutional Ownership				High Institutional Ownership			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.50	-0.08	3.89	0.05	3.56	-0.05	3.89	0.04
2	3.59	-0.06	3.78	-0.01	3.66	-0.04	3.84	0.02
3	3.73	-0.03	3.69	-0.06	3.79	-0.02	3.79	-0.01
4	3.87	-0.04	3.64	-0.07	3.91	-0.01	3.74	-0.05
Short	4.03	-0.02	3.71	-0.14	4.09	0.04	3.73	-0.09
Long – Short	-0.53***	-0.06***	0.17***	0.19***	-0.54***	-0.09***	0.15***	0.12***
(*t*-stat)	(-21.44)	(-2.75)	(5.15)	(8.40)	(-10.48)	(-7.76)	(4.51)	(4.88)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.55%	0.29%	0.56%	0.64%	0.27%	0.08%	0.29%	0.39%
	(2.94)	(1.39)	(4.47)	(4.31)	(1.87)	(0.69)	(2.39)	(2.98)
Short	-0.98%	-0.63%	-1.22%	-0.68%	-0.69%	-0.18%	-0.91%	-0.44%
	(-4.33)	(-2.98)	(-5.17)	(-3.48)	(-4.07)	(-1.10)	(-3.89)	(-2.60)
Consistent	1.18%		1.24%		0.46%		0.74%	
	(4.47)		(5.61)		(2.67)		(3.31)	
Inconsistent	1.27%		1.86%		0.77%		1.29%	
	(4.82)		(6.63)		(3.50)		(5.49)	
Diff: Incon – Con	0.09%		0.63%		0.32%		0.55%	
	(0.36)		(1.98)		(1.45)		(2.37)	

Table 13: Subsample tests based on investor sentiment

This table reports the results for sub-periods based on investor sentiment. We divide the sample into low and high sentiment periods based on the median value of Baker and Wurgler (2006) sentiment index. Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing scores MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	Low Sentiment				High Sentiment			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.49	-0.08	3.79	0.03	3.55	-0.06	3.96	0.05
2	3.59	-0.06	3.77	0.00	3.66	-0.05	3.87	0.01
3	3.70	0.00	3.72	-0.02	3.81	-0.04	3.80	-0.03
4	3.80	-0.01	3.64	-0.05	3.96	-0.02	3.71	-0.08
Short	3.98	0.01	3.64	-0.10	4.14	0.02	3.74	-0.12
Long – Short	-0.48***	-0.08***	0.15***	0.13***	-0.59***	-0.08***	0.22***	0.17***
(*t*-stat)	(-19.87)	(-5.82)	(3.79)	(2.76)	(-15.87)	(-5.76)	(10.09)	(8.57)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.35%	0.14%	0.27%	0.29%	0.38%	0.09%	0.46%	0.52%
	(2.09)	(1.27)	(1.70)	(2.56)	(2.11)	(0.62)	(2.78)	(3.37)
Short	-0.43%	-0.22%	-0.46%	-0.36%	-1.09%	-0.64%	-1.61%	-0.68%
	(-3.01)	(-1.90)	(-2.12)	(-2.22)	(-4.47)	(-3.27)	(-6.68)	(-3.52)
Consistent	0.56%		0.63%		1.02%		1.14%	
	(2.90)		(2.44)		(4.06)		(4.15)	
Inconsistent	0.56%		0.75%		1.19%		2.14%	
	(2.52)		(3.45)		(3.93)		(6.78)	
Diff: Incon – Con	0.00%		0.12%		0.17%		0.99%	
	(0.00)		(0.40)		(0.60)		(3.19)	

Online Appendix to "Security Analysts and Capital Market Anomalies"

Table A1: Analyst consensus recommendations one quarter before the construction of anomaly portfolios

This table reports the average level (Column "Rec") and change (Column "ΔRec") of consensus recommendations for quintile portfolios sorted by the anomaly variables. Reported are analyst recommendations available one quarter before the construction of the anomaly variable. We classify 11 anomalies into two clusters following Stambaugh and Yuan (2017). MGMT (PERF) stands for the composite mispricing measure of the first (second) cluster. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

Panel A: Cluster 1

	MGMT		NSI		CEI		Accrual	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.50	-0.05	3.59	-0.09	3.51	-0.06	3.67	-0.04
2	3.62	-0.04	3.62	-0.04	3.58	-0.07	3.64	-0.05
3	3.75	-0.04	3.71	-0.03	3.71	-0.11	3.75	-0.03
4	3.89	-0.03	3.86	-0.01	3.87	-0.04	3.88	0.00
Short	4.08	-0.01	4.01	0.00	4.00	0.02	4.05	-0.02
Long – Short	-0.57***	-0.03***	-0.42***	-0.09***	-0.49***	-0.09***	-0.38***	-0.03*
(*t*-stat)	(-13.07)	(-2.93)	(-12.38)	(-6.78)	(-11.21)	(-8.08)	(-8.79)	(-1.78)

	NOA		AG		IA	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.70	-0.03	3.59	-0.03	3.67	0.02
2	3.70	-0.03	3.60	-0.04	3.73	-0.03
3	3.69	-0.03	3.72	-0.05	3.76	-0.05
4	3.76	-0.04	3.87	-0.04	3.85	-0.05
Short	3.99	-0.05	4.06	-0.02	3.98	-0.05
Long – Short	-0.28***	0.02***	-0.47***	-0.01	-0.31***	0.07***
(*t*-stat)	(-10.85)	(6.48)	(-9.79)	(-0.74)	(-6.69)	(4.54)

Panel B: Cluster 2

	PERF		Distress		O-score		MOM	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.89	0.03	3.81	-0.01	3.85	-0.05	3.91	0.09
2	3.83	0.00	3.81	-0.01	3.79	-0.01	3.76	0.01
3	3.75	-0.03	3.79	-0.02	3.75	-0.02	3.71	-0.01
4	3.67	-0.06	3.70	-0.04	3.75	-0.03	3.68	-0.08
Short	3.68	-0.11	3.60	-0.09	3.84	-0.03	3.71	-0.20
Long – Short	0.21***	0.14***	0.21***	0.08***	0.02	-0.02	0.20***	0.29***
(*t*-stat)	(7.34)	(5.76)	(12.33)	(3.53)	(0.40)	(-1.42)	(6.36)	(9.75)

	GP		ROA	
	Rec	ΔRec	Rec	ΔRec
Long	3.82	-0.03	3.92	0.02
2	3.82	-0.03	3.82	-0.01
3	3.81	-0.03	3.74	-0.03
4	3.72	-0.03	3.61	-0.07
Short	3.67	-0.05	3.79	-0.09
Long – Short	0.15***	0.02**	0.13***	0.11***
(*t*-stat)	(6.81)	(2.19)	(2.78)	(3.95)

Table A2: Price run-up of anomaly portfolios during the formation period conditional on analyst recommendations at the end of June of year *t*

This table reports the buy-and-hold cumulative abnormal returns (CARs) of anomaly portfolios during the entire portfolio formation window (July of year *t* -1 to June of year *t*). At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations available at the end of June of year *t* and independently into quintiles based on anomaly characteristics at the end of June of year *t*. The CAR is calculated as the individual stock buy-and-hold cumulative return minus the cumulative value-weighted market index return, and then averaged to portfolio level. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Long×RecUp – Long×RecDown (Short×RecUp – Short×RecDown) reports the difference in the CARs between stocks with the most favorable and most unfavorable consensus recommendations for the long-leg portfolio (short-leg portfolio). Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The Newey-West adjusted t-statistics are shown in parentheses. The sample period is from 1993 to 2014.

Panel A: Cluster 1

	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	30.07%	12.89%	1.32%	18.27%	7.46%	-1.97%	18.37%	9.81%	1.60%	28.96%	12.53%	-1.44%
	(4.55)	(3.60)	(0.44)	(3.78)	(2.41)	(-0.52)	(4.67)	(2.57)	(0.43)	(4.42)	(3.52)	(-0.40)
Short	23.60%	8.64%	-10.90%	28.80%	10.61%	-6.96%	25.01%	13.56%	-5.14%	30.07%	13.93%	-8.13%
	(6.22)	(4.18)	(-1.79)	(8.62)	(4.86)	(-1.45)	(5.18)	(5.82)	(-1.54)	(7.78)	(4.60)	(-1.24)
Long×RecUp – Long×RecDown		28.76%			20.24%			16.77%			30.41%	
		(6.08)			(4.76)			(5.92)			(5.04)	
Short×RecUp – Short×RecDown		34.50%			35.76%			30.15%			38.20%	
		(5.20)			(6.45)			(4.95)			(5.01)	

	NOA			AG			IA		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	30.31%	14.39%	1.23%	32.88%	13.06%	0.00%	34.90%	18.43%	3.34%
	(5.97)	(4.16)	(0.42)	(5.45)	(3.38)	(0.00)	(6.17)	(5.57)	(0.94)
Short	19.78%	4.01%	-11.43%	25.95%	9.59%	-9.69%	21.40%	6.14%	-10.96%
	(6.44)	(1.65)	(-2.28)	(9.06)	(4.65)	(-1.74)	(5.56)	(2.77)	(-1.96)
Long×RecUp – Long×RecDown		29.08%			32.89%			31.56%	
		(20.40)			(7.28)			(7.15)	
Short×RecUp – Short×RecDown		31.22%			35.63%			32.36%	
		(6.34)			(5.65)			(4.91)	

Table A2 (Continued): Price run-up of anomaly portfolios during the formation period conditional on analyst recommendations at the end of June of year *t*

Panel B: Cluster 2

	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	48.63%	32.64%	23.50%	21.08%	12.71%	5.90%	23.41%	9.77%	-4.16%	78.10%	67.50%	58.25%
	(7.36)	(7.53)	(6.41)	(5.50)	(4.31)	(2.14)	(4.72)	(3.83)	(-0.91)	(8.65)	(9.96)	(14.13)
Short	3.74%	-12.64%	-20.39%	3.93%	-3.91%	-9.12%	34.08%	19.34%	-3.34%	-35.23%	-38.51%	-41.73%
	(1.14)	(-4.28)	(-7.28)	(1.22)	(-1.23)	(-2.92)	(6.20)	(4.17)	(-0.85)	(-11.01)	(-12.04)	(-11.95)
Long×RecUp – Long×RecDown		25.13%			15.17%			27.57%			19.84%	
		(3.70)			(5.07)			(3.92)			(2.78)	
Short×RecUp – Short×RecDown		24.12%			13.05%			37.42%			6.51%	
		(26.40)			(6.37)			(8.34)			(7.62)	

	GP			ROA		
	Up	Middle	Down	Up	Middle	Down
Long	33.03%	12.68%	-3.13%	41.77%	22.60%	13.06%
	(5.54)	(3.97)	(-0.71)	(7.01)	(6.11)	(3.44)
Short	18.33%	8.31%	0.00%	20.53%	3.88%	-15.44%
	(4.89)	(2.21)	(0.00)	(5.84)	(1.20)	(-4.26)
Long×RecUp – Long×RecDown		36.15%			28.71%	
		(5.69)			(4.88)	
Short×RecUp – Short×RecDown		18.33%			35.96%	
		(17.81)			(7.95)	

Table A3: Mutual fund net buys in anomaly portfolios conditional on analyst recommendations one quarter ago

This table reports the change of stock ownership by mutual funds (mutual fund net buys) over the period from the end of March to the end of June of year *t*. We sort stocks into three groups based on the level of analyst consensus recommendations available at the end of March of year *t* and independently into quintiles based on anomaly characteristics at the end of June of year *t*. Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Long×RecUp – Long×RecDown (Short×RecUp – Short×RecDown) reports the differences in mutual fund net buys between stocks with the most favorable and most unfavorable consensus recommendations for the long-leg portfolio (short-leg portfolio). Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The Newey-West adjusted t-statistics are shown in parentheses. The sample period is from 1993 to 2014.

Panel A: Cluster 1

	MGMT			NSI			CEI			Accrual		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.48%	0.22%	0.15%	0.32%	0.16%	0.17%	0.22%	0.13%	0.14%	0.65%	0.37%	0.19%
	(8.08)	(4.14)	(4.26)	(9.48)	(3.98)	(4.31)	(2.66)	(5.40)	(3.19)	(13.17)	(3.98)	(2.90)
Short	0.84%	0.61%	0.28%	0.94%	0.59%	0.26%	0.80%	0.60%	0.41%	0.74%	0.58%	0.13%
	(14.28)	(6.26)	(2.24)	(11.17)	(9.24)	(2.89)	(11.92)	(7.32)	(4.25)	(8.01)	(4.45)	(0.92)
Long×RecUp – Long×RecDown		0.33%			0.15%			0.07%			0.46%	
		(5.48)			(2.90)			(1.03)			(10.12)	
Short×RecUp – Short×RecDown		0.55%			0.68%			0.39%			0.62%	
		(4.84)			(7.06)			(5.03)			(5.15)	

	NOA			AG			IA		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.80%	0.39%	0.17%	0.55%	0.36%	0.16%	0.57%	0.29%	0.21%
	(11.23)	(5.04)	(2.98)	(6.71)	(4.65)	(3.13)	(21.77)	(3.86)	(4.34)
Short	0.59%	0.36%	0.17%	0.90%	0.64%	0.30%	0.72%	0.49%	0.18%
	(11.20)	(5.70)	(1.70)	(10.08)	(6.46)	(2.11)	(14.89)	(4.67)	(1.53)
Long×RecUp – Long×RecDown		0.63%			0.39%			0.36%	
		(13.07)			(5.43)			(6.22)	
Short×RecUp – Short×RecDown		0.42%			0.60%			0.54%	
		(3.74)			(4.90)			(5.15)	

Table A3 (continued): Mutual fund net buys in anomaly portfolios conditional on analyst recommendations one quarter ago

Panel B: Cluster 2

	PERF			Distress			O-score			MOM		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.74%	0.49%	0.29%	0.47%	0.31%	0.22%	0.58%	0.33%	0.18%	0.88%	0.66%	0.39%
	(51.38)	(10.78)	(4.71)	(12.29)	(6.86)	(6.53)	(6.68)	(3.54)	(1.85)	(11.56)	(8.41)	(6.49)
Short	0.53%	0.23%	0.08%	0.42%	0.15%	0.23%	0.63%	0.51%	0.05%	0.19%	-0.07%	-0.04%
	(4.96)	(2.81)	(1.21)	(5.62)	(1.64)	(2.19)	(5.36)	(4.27)	(0.57)	(1.18)	(-0.45)	(-0.43)
Long×RecUp – Long×RecDown		0.45%			0.24%			0.40%			0.49%	
		(6.66)			(3.67)			(4.75)			(5.30)	
Short×RecUp – Short×RecDown		0.45%			0.19%			0.58%			0.23%	
		(5.14)			(1.91)			(5.16)			(2.60)	

	GP			ROA		
	Up	Middle	Down	Up	Middle	Down
Long	0.65%	0.40%	0.20%	0.72%	0.42%	0.26%
	(9.66)	(6.01)	(2.85)	(20.75)	(7.21)	(4.52)
Short	0.70%	0.33%	0.18%	0.81%	0.42%	0.10%
	(8.80)	(4.30)	(2.78)	(8.18)	(3.57)	(1.40)
Long×RecUp – Long×RecDown		0.45%			0.46%	
		(7.17)			(5.98)	
Short×RecUp – Short×RecDown		0.52%			0.71%	
		(8.67)			(8.81)	

Table A4: The market efficiency implications of skilled analysts

This table reports the Fama and MacBeth (1973) regressions of stock returns on the anomaly characteristics interacted with "$Coverage\_skill$". The dependent variable is the monthly stock returns (in percentage). For each analyst at the end of each year, we calculate the rank correlation between stocks' recommendation values and the composite mispricing score PERF using all recommendations issued by this analyst in the past three years. We then sort all analysts into 10 deciles according to the correlation measure and define skilled analysts as those in the top decile. Then for each stock-month, we construct a measure "$Coverage\_skill$", defined as the natural logarithm of the number of skilled analysts scaled by the total number of analysts following the stock as follows:

$$Coverage\_skill = Ln[(1 + \#\ of\ skilled\ analysts)/(1 + \#\ of\ total\ analysts)].$$

We then run the Fama-MacBeth regression of stock returns on the anomaly,$Coverage\_skill$, and the interaction between $Coverage\_skill$ and the anomaly. We multiply the anomaly variable by -1 for Momentum, Gross Profitability, and ROA, so that a higher value of an anomaly always indicates more overpricing. We control for firm size and stock turnover, and their interactions with the anomaly. The Newey-West adjusted *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cluster 1							
	MGMT	NSI	CEI	Accrual	NOA	AG	IA
Coverage_skill×Anomaly	0.02***	0.78***	0.85***	0.68***	-0.12	0.20**	0.11
	(4.84)	(2.78)	(3.06)	(2.92)	(-1.38)	(2.56)	(0.40)
Anomaly	-0.20***	-8.64***	-10.74***	-8.62***	-0.10	-2.73***	-4.70**
	(-8.70)	(-7.11)	(-4.36)	(-5.97)	(-0.12)	(-7.18)	(-2.52)
Coverage_skill	0.71***	1.46***	1.31***	1.75***	1.68***	1.54***	1.70***
	(3.53)	(10.00)	(10.18)	(10.37)	(11.32)	(10.42)	(10.61)
Ln(Size)×Anomaly	0.02***	0.76***	0.92***	0.77***	-0.00	0.24***	0.38**
	(8.79)	(6.89)	(4.23)	(6.02)	(-0.00)	(6.82)	(2.39)
Turnover×Anomaly	-0.06***	-5.80***	-0.70	-1.52	-0.87*	-0.25	-2.79**
	(-2.87)	(-2.70)	(-0.21)	(-1.46)	(-1.95)	(-0.40)	(-2.59)
Ln(Size)	0.23**	1.01***	0.92***	1.19***	1.09***	1.04***	1.14***
	(2.47)	(11.64)	(10.90)	(12.54)	(13.35)	(11.85)	(12.01)
Turnover	3.31	-0.22	-0.77	-0.48	-0.05	-0.47	0.09
	(1.53)	(-0.17)	(-0.53)	(-0.38)	(-0.04)	(-0.37)	(0.07)
Intercept	-0.73	-9.60***	-8.64***	-11.55***	-10.42***	-9.99***	-11.07***
	(-0.59)	(-8.60)	(-7.71)	(-9.35)	(-10.01)	(-8.86)	(-8.96)
Observations	668,865	650,129	605,441	513,929	667,793	669,836	575,196
Adjusted R^2	0.053	0.048	0.050	0.052	0.050	0.050	0.049

Table A4 (continued): The market efficiency implications of skilled analysts

Panel B: Cluster 2						
	PERF	Distress	O-score	MOM	GP	ROA
Coverage_skill×Anomaly	0.01***	0.11	0.17***	-0.10	-0.21	5.43***
	(2.63)	(0.97)	(7.40)	(-0.55)	(-0.92)	(3.70)
Anomaly	-0.19***	-5.46***	-2.57***	-1.01	-1.59	-105.40***
	(-9.10)	(-6.38)	(-13.69)	(-0.82)	(-1.09)	(-11.31)
Coverage_skill	1.09***	2.20**	2.38***	1.26***	1.56***	1.65***
	(5.86)	(2.44)	(11.92)	(9.97)	(8.91)	(10.77)
Ln(Size)×Anomaly	0.02***	0.47***	0.23***	0.06	0.06	8.90***
	(8.03)	(6.20)	(14.01)	(0.52)	(0.46)	(10.67)
Turnover×Anomaly	-0.10***	-4.12***	-0.75***	0.75	-5.05***	-15.56**
	(-4.11)	(-2.67)	(-5.30)	(0.88)	(-3.34)	(-1.98)
Ln(Size)	0.30***	4.89***	2.11***	0.86***	1.13***	1.23***
	(2.62)	(7.59)	(15.56)	(10.91)	(11.94)	(13.43)
Turnover	3.51**	-35.59***	-3.20**	-1.65	-2.75*	-0.85
	(2.49)	(-2.70)	(-2.29)	(-1.23)	(-1.73)	(-0.65)
Intercept	-0.85	-54.80***	-21.88***	-8.23***	-11.24***	-12.11***
	(-0.61)	(-7.64)	(-12.99)	(-7.87)	(-9.90)	(-10.55)
Observations	661,412	359,496	522,326	616,331	673,591	691,037
Adjusted R^2	0.056	0.058	0.057	0.062	0.052	0.053

Table A5: Subsample tests based on trading costs (daily percentage quoted spreads)

This table reports the results for subsamples based on trading costs. We divide stocks equally into the high and low trading cost groups each month, where the trading cost is measured by the daily percentage quoted spread following Chung and Zhang (2014). Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing measures MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations, and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	High Trading Cost				Low Trading Cost			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.57	-0.06	4.02	0.07	3.49	-0.07	3.86	0.04
2	3.67	-0.06	3.91	0.01	3.60	-0.05	3.80	0.01
3	3.81	-0.03	3.79	-0.04	3.73	-0.02	3.74	-0.02
4	3.94	-0.03	3.71	-0.09	3.87	-0.02	3.67	-0.05
Short	4.11	-0.01	3.71	-0.13	4.04	0.03	3.67	-0.10
Long – Short	-0.54***	-0.06***	0.30***	0.20***	-0.55***	-0.09***	0.19***	0.13***
(*t*-stat)	(-20.38)	(-3.35)	(11.73)	(9.39)	(-14.13)	(-7.33)	(6.23)	(4.75)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.50%	0.20%	0.58%	0.77%	0.28%	0.14%	0.30%	0.43%
	(2.39)	(1.32)	(3.75)	(5.51)	(2.33)	(1.25)	(2.23)	(3.52)
Short	-0.65%	-0.61%	-1.21%	-0.77%	-0.83%	-0.44%	-0.95%	-0.37%
	(-3.42)	(-4.23)	(-4.57)	(-4.30)	(-4.16)	(-2.61)	(-4.14)	(-2.52)
Consistent	1.11%		1.35%		0.72%		0.67%	
	(4.55)		(6.58)		(3.76)		(2.96)	
Inconsistent	0.85%		1.98%		0.97%		1.38%	
	(3.39)		(7.69)		(3.72)		(4.44)	
Diff: Incon – Con	-0.26%		0.62%		0.25%		0.71%	
	(-1.05)		(2.41)		(0.96)		(2.45)	

Table A6: Subsample tests based on ownership by dedicated institutional investors

This table reports the results for subsamples based on dedicated institutional investor ownership. We divide stocks into the high and low institutional ownership groups according to the median ownership by dedicated institutions in the last quarter following the classification of Bushee (1998) and Bushee and Noe (2000). Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two composite mispricing scores MGMT or PERF. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel B reports the monthly Fama-French three-factor alphas of portfolios sorted independently by anomaly characteristics and the level of analyst consensus recommendations. At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations, and independently into quintiles based on the composite mispricing measures. Up (Down) refers to stocks in the top (bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	Low Dedicated Institutional Ownership				High Dedicated Institutional Ownership			
Panel A: Recommendation level or change								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.52	-0.06	3.91	0.05	3.53	-0.07	3.87	0.03
2	3.63	-0.04	3.84	0.02	3.64	-0.06	3.83	0.00
3	3.76	-0.01	3.74	-0.03	3.77	-0.03	3.77	-0.03
4	3.90	-0.01	3.67	-0.06	3.89	-0.03	3.71	-0.06
Short	4.07	0.01	3.71	-0.10	4.06	0.02	3.71	-0.12
Long – Short	-0.55***	-0.07***	0.20***	0.15***	-0.53***	-0.09***	0.16***	0.15***
(*t*-stat)	(-18.85)	(-4.37)	(5.73)	(7.23)	(-15.38)	(-8.91)	(5.52)	(5.47)
Panel B: Double sorts (Fama-French three-factor alphas)								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.54%	0.27%	0.36%	0.41%	0.19%	0.04%	0.36%	0.46%
	(3.57)	(1.93)	(3.20)	(3.49)	(1.60)	(0.35)	(2.79)	(3.06)
Short	-0.96%	-0.66%	-1.11%	-0.59%	-0.73%	-0.16%	-0.98%	-0.42%
	(-4.57)	(-3.40)	(-4.31)	(-3.88)	(-4.42)	(-0.75)	(-4.60)	(-2.67)
Consistent	1.21%		0.95%		0.35%		0.77%	
	(4.33)		(4.96)		(1.53)		(3.71)	
Inconsistent	1.23%		1.53%		0.77%		1.45%	
	(4.76)		(5.08)		(4.07)		(5.70)	
Diff: Incon – Con	0.02%		0.57%		0.42%		0.67%	
	(0.10)		(1.87)		(1.74)		(2.66)	

Table A7: Informativeness of six alternative anomalies

This table reports the average monthly returns and Fama-French three-factor alphas for the long-short portfolios of the six alternative anomalies, including idiosyncratic volatility (IVOL), maximum daily return in the last month (MaxReturn), past 12-month average turnover (Turnover), cash flow duration (Duration), long-run reversal (LMW), and market beta (Beta). Panel A reports the raw returns and Panel B reports the Fama-French three-factor alphas. The *t*-statistics in parentheses are based on Newey-West standard errors. The sample period is from 1993 to 2014.

	IVOL	MaxReturn	Turnover	Duration	LMW	Beta
Panel A: Raw returns						
Long	0.94%	0.95%	1.04%	1.08%	1.39%	0.65%
	(3.62)	(3.38)	(2.62)	(2.45)	(2.33)	(2.34)
Short	0.35%	0.70%	0.59%	0.88%	0.67%	1.23%
	(0.64)	(1.03)	(1.07)	(1.31)	(1.62)	(1.80)
Long – Short	0.59%	0.25%	0.45%	0.20%	0.72%	-0.58%
(*t*-stat)	(1.35)	(0.48)	(1.37)	(0.52)	(2.05)	(-1.08)
Panel B: Fama-French three-factor alphas						
Long	0.34%	0.36%	0.37%	0.17%	0.30%	0.08%
	(0.20)	(0.23)	(0.48)	(0.60)	(1.05)	(0.39)
Short	-0.72%	-0.46%	-0.53%	-0.25%	-0.19%	-0.05%
	(-1.15)	(-1.21)	(-0.87)	(-1.16)	(-0.51)	(-1.12)
Long – Short	1.06%	0.82%	0.90%	0.42%	0.49%	0.12%
(*t*-stat)	(5.65)	(3.08)	(4.28)	(1.85)	(1.66)	(0.37)

Table A8: Analyst consensus recommendations for six alternative anomalies

This table reports the average level and change of consensus recommendations for quintile portfolios sorted by the six alternative anomalies, including idiosyncratic volatility (IVOL), maximum daily return in the last month (MaxReturn), past 12-month average turnover (Turnover), cash flow duration (Duration), long-run reversal (LMW), and market beta (Beta). Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. The *t*-statistics in parentheses are based on Newey-West standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993 to 2014.

	IVOL		MaxReturn		Turnover		Duration	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.59	-0.03	3.65	-0.04	3.70	-0.05	3.68	-0.09
2	3.73	-0.02	3.74	-0.04	3.74	-0.06	3.71	-0.06
3	3.82	-0.03	3.80	-0.04	3.75	-0.05	3.78	-0.03
4	3.88	-0.02	3.84	-0.05	3.79	-0.05	3.84	-0.01
Short	3.92	-0.05	3.80	-0.12	3.81	-0.06	3.81	-0.10
Long – Short	-0.33***	0.01	-0.15***	0.08**	-0.11	0.01	-0.13***	0.01
(*t*-stat)	(-10.38)	(0.43)	(-5.33)	(2.39)	(-1.56)	(0.58)	(-6.35)	(0.62)

	LMW		Beta	
	Rec	ΔRec	Rec	ΔRec
Long	3.50	-0.14	3.63	-0.05
2	3.60	-0.07	3.67	-0.04
3	3.67	-0.03	3.74	-0.03
4	3.78	-0.01	3.79	-0.05
Short	4.00	0.05	3.80	-0.06
Long – Short	-0.49***	-0.19***	-0.17***	0.00
(*t*-stat)	(-10.65)	(-8.09)	(-6.14)	(0.10)

Table A9: Abnormal returns of alternative anomaly portfolios conditional on analyst recommendations

This table reports the monthly Fama-French three-factor alphas of portfolios sorted independently by the six alternative anomalies and the level of analyst consensus recommendations. At the end of each June, we sort stocks into three groups based on the level of analyst consensus recommendations, and independently into quintiles based on anomaly characteristics. The six anomalies are idiosyncratic volatility (IVOL), maximum daily return in the last month (MaxReturn), past 12-month average turnover (Turnover), cash flow duration (Duration), long-run reversal (LMW), and market beta (Beta). Up (Middle, Down) refers to stocks in the top (middle, bottom) tercile based on analyst consensus recommendations. Long (Short) refers to stocks in the most undervalued (overvalued) quintile based on anomaly characteristics. Consistent (Inconsistent) refers to the long-short portfolio where analyst recommendations are in congruent with (contradictory to) the anomaly prescriptions. Diff is the difference in alphas between Inconsistent and Consistent portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors. The sample period is from 1993 to 2014.

	IVOL			MaxReturn			Turnover			Duration		
	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down	Up	Middle	Down
Long	0.42%	0.33%	0.35%	0.42%	0.35%	0.36%	0.04%	0.12%	0.39%	-0.02%	0.16%	0.32%
	(2.96)	(2.94)	(3.58)	(2.73)	(2.52)	(3.00)	(0.18)	(0.53)	(3.72)	(-0.11)	(0.66)	(1.90)
Short	-0.94%	-0.56%	-0.45%	-0.90%	-0.31%	-0.08%	-0.77%	-0.33%	-0.47%	-0.65%	0.00%	0.02%
	(-6.65)	(-3.75)	(-2.85)	(-3.56)	(-1.28)	(-0.29)	(-4.73)	(-2.04)	(-1.94)	(-2.27)	(0.01)	(0.06)
Consistent		0.87%			0.50%			0.51%			-0.05%	
		(3.63)			(1.60)			(1.79)			(-0.15)	
Inconsistent		1.29%			1.26%			1.16%			0.97%	
		(6.82)			(4.84)			(5.88)			(3.98)	
Diff: Incon – Con		0.42%			0.76%			0.64%			1.02%	
		(1.98)			(3.56)			(2.48)			(3.81)	

	LMW			Beta		
	Up	Middle	Down	Up	Middle	Down
Long	0.23%	0.22%	0.30%	0.11%	0.15%	0.00%
	(1.55)	(0.76)	(0.90)	(0.76)	(1.14)	(-0.01)
Short	-0.28%	-0.08%	-0.12%	-0.44%	0.03%	0.23%
	(-1.87)	(-0.46)	(-0.50)	(-1.65)	(0.10)	(0.63)
Consistent		0.34%			-0.11%	
		(0.98)			(-0.28)	
Inconsistent		0.58%			0.44%	
		(1.89)			(1.53)	
Diff: Incon – Con		0.24%			0.55%	
		(1.14)			(2.00)	

Table A10: Unconditional return predictability of analyst consensus recommendations

This table reports the monthly raw returns and Fama-French three-factor alphas of quintile portfolios sorted by the level and change of analyst consensus recommendations. At the beginning of every quarter (month), we sort stocks into quintiles based on the level or change of recommendations observed at the end of last quarter (month) and re-balance the portfolio quarterly (monthly). Panel A (B) reports the raw returns for the quarterly (monthly) re-balanced portfolios. Panel C (D) reports the Fama-French three-factor alphas for quarterly (monthly) re-balanced portfolios. The *t*-statistics in parentheses are based on Newey-West standard errors.

Panel A: Quarterly rebalanced portfolios (Raw returns)								
	1993 - 2000		2001 - 2007		2008 - 2014		1993 - 2014	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Short	0.46%	0.60%	1.00%	0.74%	0.94%	1.10%	0.80%	0.82%
2	0.76%	1.10%	0.83%	0.99%	1.06%	0.94%	0.88%	1.01%
3	0.88%	0.91%	1.04%	0.80%	1.09%	1.02%	1.00%	0.91%
4	0.40%	0.94%	0.55%	0.83%	0.92%	1.05%	0.62%	0.94%
Long	0.31%	1.02%	0.56%	0.85%	0.82%	1.07%	0.56%	0.98%
Long – Short	-0.14%	0.43%	-0.44%	0.11%	-0.12%	-0.03%	-0.23%	0.16%
(*t*-stat)	(-0.44)	(2.23)	(-1.30)	(0.47)	(-0.61)	(-0.14)	(-1.23)	(1.11)

Panel B: Monthly rebalanced portfolios (Raw returns)								
	1993 - 2000		2001 - 2007		2008 - 2014		1993 - 2014	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Short	0.46%	0.48%	1.01%	0.74%	0.93%	1.01%	0.80%	0.76%
2	0.68%	1.00%	0.71%	0.92%	1.03%	0.95%	0.81%	0.96%
3	0.90%	0.96%	1.13%	0.80%	1.08%	1.03%	1.03%	0.93%
4	0.46%	0.79%	0.58%	0.83%	0.96%	1.04%	0.66%	0.89%
Long	0.52%	1.17%	0.64%	0.87%	0.86%	1.18%	0.67%	1.07%
Long – Short	0.06%	0.69%	-0.37%	0.13%	-0.06%	0.16%	-0.13%	0.31%
(*t*-stat)	(0.18)	(3.15)	(-1.10)	(0.53)	(-0.31)	(0.89)	(-0.65)	(2.46)

Table A10 (continued): Unconditional return predictability of analyst consensus recommendations

Panel C: Quarterly rebalanced portfolios (Fama-French three-factor alphas)								
	1993-2000		2001 - 2007		2008 - 2014		1993 - 2014	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Short	-0.50%	-0.59%	0.32%	0.07%	0.04%	0.10%	-0.08%	-0.14%
2	-0.36%	-0.24%	0.10%	0.36%	0.09%	0.02%	-0.06%	0.08%
3	-0.14%	-0.49%	0.35%	0.13%	0.05%	0.06%	0.12%	-0.04%
4	-0.55%	-0.34%	0.08%	0.20%	-0.12%	0.00%	-0.23%	-0.01%
Long	-0.76%	-0.26%	-0.06%	0.20%	-0.27%	0.04%	-0.30%	0.06%
Long – Short	-0.25%	0.33%	-0.38%	0.13%	-0.31%	-0.06%	-0.22%	0.20%
(*t*-stat)	(-1.61)	(3.09)	(-1.42)	(0.54)	(-1.50)	(-0.30)	(-1.90)	(1.98)

Panel D: Monthly rebalanced portfolios (Fama-French three-factor alphas)								
	1993-2000		2001 - 2007		2008 - 2014		1993 - 2014	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Short	-0.51%	-0.85%	0.31%	0.08%	0.03%	0.01%	-0.09%	-0.23%
2	-0.44%	-0.32%	0.01%	0.31%	0.07%	0.02%	-0.13%	0.02%
3	-0.13%	-0.43%	0.43%	0.12%	0.02%	0.07%	0.14%	-0.03%
4	-0.51%	-0.43%	0.11%	0.20%	-0.07%	0.00%	-0.18%	-0.05%
Long	-0.58%	-0.17%	0.02%	0.22%	-0.22%	0.13%	-0.20%	0.14%
Long – Short	-0.07%	0.68%	-0.29%	0.15%	-0.25%	0.12%	-0.11%	0.37%
(*t*-stat)	(-0.41)	(3.25)	(-1.04)	(0.58)	(-1.17)	(0.80)	(-0.92)	(3.49)