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Security analysts and capital market anomalies

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Security Analysts and Capital Market Anomalies[*]

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Abstract

We examine whether analysts use information in well-known stock return anomalies when making recommendations. We find results contrary to the common view that analysts are sophisticated information intermediaries who help improve market efficiency. Specifically, when analysts make more favorable recommendations to stocks classified as overvalued, these stocks tend to have particularly large negative abnormal returns ex post. Moreover, analysts whose recommendations are more aligned with anomaly signals are more skilled and elicit greater recommendation announcement returns. Our results suggest that analysts' biased recommendations could be a source of market frictions that impede the efficient correction of mispricing.

JEL classification: G12, G14

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Abstract

We examine whether analysts use information in well-known stock return anomalies when making recommendations. We find results contrary to the common view that analysts are sophisticated information intermediaries who help improve market efficiency. Specifically, when analysts make more favorable recommendations to stocks classified as overvalued, these stocks tend to have particularly large negative abnormal returns ex post. Moreover, analysts whose recommendations are more aligned with anomaly signals are more skilled and elicit greater recommendation announcement returns. Our results suggest that analysts' biased recommendations could be a source of market frictions that impede the efficient correction of mispricing.

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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 long-standing 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 et al., 2001). 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, to generate trading commissions, or to curry favor with management for access to private information compromise their integrity and objectivity (Lin and McNichols, 1998; Chen and Matsumoto, 2006; Cowen, Groysberg, and Healy, 2006). 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 may upwardly bias their forecasts or recommendations in anticipation of future business. In addition to conflicts of interest arising from investment banking/brokerage affiliations, analyst recommendations or forecasts may be biased for non-strategic reasons (La Porta, 1996).

In this paper, we address this important question by examining whether analysts exploit well-documented stock return anomalies when making recommendations. Over the past several decades, researchers have discovered numerous cross-sectional stock return anomalies. Irrespective of the sources of return predictability, these anomalies represent publically 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.[1]

We propose two competing views on 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. More 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 strategically follow analyst recommendations.[2] In other words, biased analyst recommendations are a potential source of market frictions that contribute to sustained mispricing.

Following Stambaugh, Yu, and Yuan (2012; 2015), we construct 11 prominent asset pricing anomalies using the sample with 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

[1] 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.
[2] 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 (2014) show that mutual funds tend to herd into with consensus sell-side analyst upgrades, and herd out of stocks with consensus downgrades, and that herding by career-concerned fund managers is price destabilizing.

monthly three-factor alphas of 0.86% and 0.99%, respectively.[3] This strong return predictability suggests that anomaly signals should be part of the information set that analysts can use when making their 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.[4] 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 particularly strong for anomalies related to equity issuance and investment. For example, for MGMT, the mean recommendation value is 4.09 for stocks in the short leg and 3.53 for stocks in the long leg with a difference of -0.56, which is highly significant. By contrast, analyst recommendations seem to be more consistent with the 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. It suggests that analysts are actively revising opinions on anomaly stocks, but their views tend to be in the wrong direction of anomaly predictions. Thus, analyst inattention or stale recommendation story cannot fully explain our findings.

The differential analyst behavior across the two categories of anomalies is consistent with previous literature that finds that analysts tend to issue overly optimistic growth forecasts or recommendations for firms characterized with high growth, large capital spending, and equity financing needs. These firms are more likely to be potential investment banking clients of the

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

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

brokerage firms employing the analysts. Analysts are also likely to issue more favorable recommendations for better performing firms with high profitability or past winners.

However, analyst recommendation behavior itself is not sufficient to distinguish between 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 can offset that of anomalies. We therefore examine anomaly returns when analyst recommendations confirm or contradict anomaly signals. The result reveals the same message. When analyst recommendations and anomaly prescriptions contradict, anomaly returns are amplified, especially for the anomalies associated with PERF. The abnormal returns in inconsistent cases are larger than those in consistent cases for all 11 anomalies, and significantly so for 7 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 favorable recommendations, which earns a particularly large negative return. This is consistent with the idea that short selling overvalued stocks is costlier than correcting underpriced stocks (Nagel, 2005; Stambaugh et al., 2015), especially when betting against analyst consensus. The amplification effect of analyst recommendations on anomalies is not driven by other firm characteristics. The result from Fama and MacBeth (1973) regressions is similar, as we also control for standard return predictors.

The preceding finding may mask heterogeneity across individual analysts who differ significantly in their skills and incentives to generate informative recommendations. To shed light on this issue, for each analyst we calculate the correlation between her recommendation values and the two composite mispricing scores among all of the stocks covered by the analyst during the past three years. Consistent with the idea that this correlation metric captures analysts' skill or unbiasedness, we find that analysts with a higher correlation metric elicit stronger market reactions when announcing recommendation changes.

We conduct several tests to rule out alternative explanations. First, analysts may simply be unaware of the return predictability of these anomalies before their discoveries 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 can be reluctant to incorporate anomaly signals into their recommendations as 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, suggesting that limits-to-arbitrage concerns on the part of analysts is unlikely to explain our findings. Third, 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 incentive 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 high- rather than low-sentiment periods. 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 over an earlier sample period, Barber et al. (2001) and Jegadeesh et al. (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 re-examine 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 seemingly contradictory results of our paper with those of prior studies are mainly attributable to the different sample periods studied by these papers.

In a recent concurrent working paper, Engelberg, McLean, and Pontiff (2018b) document similar evidence 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 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 over the last 40 years. Although the sources of return predictability of these anomalies are under debate, the large abnormal returns generated by some of these anomalies are well established. In this subsection, we start with the 11 prominent anomalies extensively examined by Stambaugh et al. (2012; 2015) 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 2 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 (I/A). 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 name the pricing factor arising from this average ranking score as MGMT. The second cluster of anomalies includes gross profitability (GP), return on assets (ROA), momentum (MOM), distress (Distress), and O-score. These five anomaly variables are more related to firm performance and less directly controlled by management. Stambaugh and Yuan (2017) denote the pricing factor generated from this cluster as PERF. We describe each anomaly in detail as follows:

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).

(3) Accounting accruals (Accrual): Sloan (1996) documents 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 (I/A): 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) Gross profitability (GP): Novy-Marx (2012) 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, Sun, Wei, and Xie (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 3-12 months continue to perform well in the next 3-12 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 have examined an increasingly larger 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 fell after 2003. Similarly, McLean and Pontiff (2016) find that the return predictability of 97 variables shown to predict cross-sectional stock returns declined significantly post-publications, suggesting that investors learn about mispricing from academic studies. However, Yan and Zheng (2017) evaluate 18,000 fundamental signals from financial statements, show that many signals are significant predictors of cross-sectional stock returns even after accounting for data mining, and suggest that anomalies are better explained by mispricing. Engelberg, McLean, Pontiff (2018a) document that anomaly returns are many times higher on news 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. The importance of analysts' role in capital markets has spurred research showing that analysts influence the informational efficiency of capital markets.

A long-standing question in the finance and accounting literature examines 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 recommendation changes illicit 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 document 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 recommendation 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.[5] For example, McNichols and O'Brien (1997) report that the distribution of analysts' buy/sell recommendations is positively skewed

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

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 or under- or over-reactions to analyst reports), imply that analyst research cannot be unambiguously 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.[6] They are also less likely to reveal negative news.[7]

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 structure, analysts' choices of which firms to cover should reflect their true expectation of firms' future performance.

2.3. Market participants and capital market anomalies

[6] See, for example, Dugar and Nathan (1995), Lin and McNichols (1998), and Dechow, Hutton, and Sloan (2000).
[7] See, for example, O'Brien, McNichols, and Lin (2005).

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, may contribute to the pervasiveness of these anomaly patterns. Jiang (2010) argues that herding among institutional investors contributes to the value effect. Edelen, Ince, and Kadlec (2016) find that institutional investors tend to trade contrary to anomaly prescriptions and that their trading amplifies anomaly returns. Akbas et al. (2015) find that aggregate flows into the mutual fund sector exacerbates well-known stock return anomalies, while aggregate flows into the hedge fund sector attenuate anomalies.

With the tremendous growth of the hedge fund sector in the recent 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 interests 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 recommendations data come from the I/B/E/S summary file, while the individual analyst recommendations are from the I/B/E/S detail history file. The I/B/E/S detailed recommendation data begin in December 1992 and consensus recommendations start from 1993.

Recommendation value 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 on the same firm one year ago. We merge the analyst data with the Center for Research in Security Prices (CRSP) data after eliminating firms with share codes other than 10 or 11 and firms with stock prices below $1.

Following Stambaugh and Yuan (2017), anomaly measures are constructed 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 define the long- and short legs as the extreme quintiles. When constructing the composite mispricing factors, 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.

We also calculate the correlations between individual analysts' recommendation values and two mispricing scores among stocks covered by the analyst, $Corr_{MGMT}$ and $Corr_{PERF}$. To compute the correlations, we sort stocks into quintiles based on the recommendation value and the two mispricing scores, where the highest (lowest) quintile represents the most (least) favorable analyst recommendations and the most undervalued (overvalued) stocks, respectively. We then calculate the correlation between these two ranking variables for each individual analyst in each year using her past three-year stock recommendations, namely:

$$Corr_{i,type} = \frac{\sum(Rec_{i,n} - \overline{Rec_i})(Rank_n^{type} - \overline{Rank}^{type})}{\sqrt{\sum(Rec_{i,n} - \overline{Rec_i})^2 \sum(Rank_n^{type} - \overline{Rank}^{type})^2}} \tag{1}$$

where $type$ stands for MGMT or PERF. $Rec_{i,n}$ is the n^{th} recommendation issued by analyst i in the past three years, ranging from 1 (least favorable) to 5 (most favorable). $\overline{Rec_i}$ is the mean of all recommendations issued by analyst i within the past three years. $Rank_n^{type}$ is the mispricing ranking for the n^{th} stock recommendation based on the type of the composite mispricing metric (MGMT or PERF), ranging from 1 (overvalued) to 5 (undervalued). In addition, we keep only the most recent stock recommendation of an analyst for a given firm in a given year to calculate the correlation.

We also construct variables suggested by the prior literature that are associated with the informativeness of analyst research, including analyst, recommendation, broker, and firm characteristics. Following Green et al. (2014), we use $|\Delta Rec_{individual}|$ to stand for the magnitude of the recommendation revision. $Concurrent$ is a dummy variable that equals one if a stock recommendation is accompanied by earnings forecast revision and zero otherwise, based on Kecskés, Michaely, and Womack's (2016) finding that stock recommendations accompanied by earnings forecast revisions lead to larger price reactions. Furthermore, Ivkovic and Jegadeesh (2004) find that recommendations before (after) an earnings announcement lead to greater (weaker) price responses. Therefore, to control for these effects, we create a $Pre\text{-}earnings$ ($Post\text{-}earnings$) dummy variable, which equals one if the report was issued two weeks before (after) the earnings announcement and zero otherwise. $Away$ is a dummy variable that equals one if an earnings forecast revision or a recommendation change is away from 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 an $AllStar$ analyst dummy variable. Another $Accuracy$ variable is included, as analysts with more accurate earnings forecasts produce more profitable recommendations (Loh and Mian, 2006). Mikhail, Walther, and Willis (1997) emphasize the importance of analyst experiences for forecast accuracy. As a result, we construct two experience measures: $TotalExp$ counts the number of years that an analyst has covered any stocks, and $FirmExp$ counts the number of years that the analyst has covered the specific firm. We add $Ln(BrokerSize)$ to control for the differential resources available to analysts employed by brokerage firms with different sizes (Clement 1999). Finally, we include several firm characteristics: book-to-market ratio ($Ln(B/M)$), firm size ($Ln(Size)$), short-term reversal or past one-month returns ($Return_{t\text{-}1}$), volatility, past stock returns (($MOM_{(-21,-1)}$ and $MOM_{(-252,-22)}$), and the number of analysts following ($Coverage$).

Table 1 presents the summary statistics for all of the variables with the mean, standard deviation, minimum, quartiles and maximum values reported. In general, these summary statistics are consistent with prior research. The mean value of Rec is 3.76 and the median is 4, suggesting an overall optimism of analyst consensus recommendations (otherwise, both values should be close to 3). The mean of ΔRec is negative (-0.08) in our sample, suggesting that analysts are more likely to downgrade rather than upgrade a firm. Finally, $Corr_{MGMT}$ is on average negative while

$Corr_{PERF}$ is positive, suggesting that analysts may 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 anomalies and examine the unconditional anomaly returns during the sample period when analyst recommendation data becomes available. We also construct two composite mispricing scores that combine the information of two groups of anomalies: MGMT and PERF.

Table 2 reports the long-short portfolio returns of 11 anomalies and 2 composite mispricing factors. Panel A (Panel B) reports the raw returns of the MGMT (PERF) anomalies, and Panel C (Panel D) reports the Fama and French (1993) three-factor adjusted alphas. Overall, long-short portfolios based on the 11 anomalies generate significant monthly Fama and French (1993) three-factor alphas ranging from 0.35% to 1.09%. 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, which is consistent with the literature that short selling overvalued stocks is more costly and prohibitive than taking long positions on undervalued stocks (Nagel, 2005).

[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 then test the differences in the mean analyst consensus recommendation values in the long- and short legs of the portfolios. We analyze both the level and change of recommendations across the anomaly-sorted quintile portfolios.

Table 3 reports the results. In Panel A, we find that stocks in the short leg of the anomalies receive more favorable recommendations than those in the long leg of anomalies. For example, the average recommendation value is 3.53 for the long leg of the composite mispricing score MGMT and 4.09 for its short leg. The difference of -0.56 is statistically significant at the 1% level. We find similar results across all individual anomalies belonging to the MGMT category. In fact, the level (change) of recommendation monotonically increases from the long leg to the short leg for almost all of the anomalies in the MGMT category. In sharp contrast, we find that the anomalies belonging to the PERF category suggest a different story. Analysts on average seem to issue recommendations consistent with these anomalies' predictions. The mean recommendation level is 3.91 for the long leg of the composite mispricing score PERF and 3.72 for its short leg. The difference of 0.19 is statistically significant but economically small compared with the difference of recommendations across portfolios sorted on 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 the MGMT mispricing measure and upgrade recommendations by 0.02 for the short leg. The difference in change of recommendations between long- and short-leg stocks is again highly significant. The result from the change of recommendations is particularly puzzling, because it suggests that analysts are actively issuing opinions on anomaly stocks, although their opinions tend to be in the wrong direction of the anomaly prediction. Thus, the analyst inattention and stale recommendation story cannot explain our finding.

Overall, our results suggest that analysts tend to issue more favorable recommendations to stocks with high investment growth and issuance needs, but also of higher profitability and past stock performance. Because firms with high investment rates and issuance activities have negative expected returns, the result suggests that analysts do not fully use the expected return information contained in anomalies when making stock recommendations.

4.3 Anomaly returns conditional on analyst recommendations

The inconsistence between analyst recommendation and anomaly ranking presented in the previous section is not sufficient to conclude that analyst recommendations are biased. Analysts may have superior private information beyond that contained in anomaly characteristics, so the information content of their recommendations may offset the information about the anomalies. To distinguish between 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 of the stocks based on the anomaly signals and level of recommendations. We then take the intersection of the long leg (top 20%) and short leg (bottom 20%) of each anomaly with the most and least favorable terciles of recommendations. That is, for each anomaly, we partition the long- and short-leg portfolios into stocks for which the analysts have the most favorable recommendations (top one third of recommendations) and those for which the analysts have the most unfavorable recommendations (bottom one third of recommendations). We then calculate the Fama and French (1993) three-factor alphas for each of the four portfolios. We further construct two types of long-short portfolio: 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).[8] We test the difference in the long-short portfolio returns between the consistent and inconsistent groups. The results with corresponding *t*-statistics are reported in Table 4.

[Insert Table 4 here]

Overall, the double sort results reveal the same message. The long-short portfolio alphas are larger for inconsistent portfolios than consistent portfolios for all 11 anomalies, and 7 of them are significant. The result is particularly strong for anomalies in the PERF category. For example, the long-short portfolio based on the PERF composite mispricing score 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*-stat of 3.17. The results from individual components of PERF are similar with the differences in alphas between the "inconsistent" and "consistent" groups ranging from 0.44% 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, those 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 amplify performance-related anomalies. For the MGMT anomalies where analyst recommendations on

[8] More specifically, the long-short portfolio where analyst recommendations are consistent with anomaly prescriptions refers to the strategy that longs stocks in the long leg of the anomaly portfolio with the most favorable analyst recommendations and shorts stocks in the short leg of the anomaly portfolio with the least favorable analyst recommendations. The long-short portfolio where analyst recommendations are inconsistent with anomaly predictions refers to the strategy that longs stocks in the long leg of the anomaly with the least favorable analyst recommendations and shorts stocks in the short-leg of the anomaly with the most favorable analyst recommendations.

average tend to be contradictory to the prescriptions of anomalies, although all of the differences in alphas between the "inconsistent" and "consistent" groups are positive, they are much smaller and insignificant, except in two cases: 0.54% (*t*-stat = 2.30) for Accrual and 0.51% (*t*-stat = 2.38) for IA.

Another approach complementary to portfolio sorts is to run Fama–MacBeth regressions of stock returns in month t on anomaly characteristics interacted with analyst recommendations in month t - 1. The regression approach allows us to control for other firm characteristics associated with expected returns, including market capitalization ($Ln(Size)$), the book-to-market ratio ($Ln(B/M)$), short-term reversal (stock return in month t - 1), idiosyncratic volatility ($IVOL$), past 12-month turnover ($Turnover$), analyst forecast dispersion ($Dispersion$), and max daily return in the last month ($MaxReturn$). To facilitate the interpretation of regression coefficients, we rank stocks into five groups based on anomalies and create three dummy variables, $Long$, $Short$, and Mid, which represent the long leg, short leg, and the remaining three middle portfolios, respectively. We also sort the stocks into three groups based on analyst recommendation levels, with the most favorable (unfavorable) recommendation coded as $RecUp$ ($RecDown$) and the middle as $RecMid$. The Fama–MacBeth regression is conducted as follows:

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

The regression results are reported in Table 5. Panel A reports the results for the MGMT anomalies and Panel B reports those for PERF anomalies. Overall, the results using the Fama–MacBeth regression are similar to what we document for the double-sorted portfolios. 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 generate more negative future returns when those stocks are recommended favorably by analysts. For example, column (1) of Panel A shows that stocks in the short leg of the MGMT composite mispricing score generates a 0.40% (*t*-stat = 2.16) lower return when they are associated with the most unfavorable recommendations, while the return is 0.69% (*t*-stat = 4.37) lower for the stocks associated with the most favorable recommendations. Similarly, column (1) of Panel B shows that stocks in the short leg of the PERF composite mispricing score generate a 0.44% (*t*-stat = 2.80) lower return when they are associated with the most unfavorable recommendations, while the return is 0.76% (*t*-stat = 3.19) lower for the stocks associated with the most favorable recommendations.

[Insert Table 5 here]

4.4 Earnings announcement returns

In this section, we further examine the earnings announcement returns of the double-sorted portfolios based on analyst recommendations and anomaly characteristics. The earnings announcement setting is especially useful for distinguishing between mispricing and risk-based explanations for our results, as short-run abnormal returns around earnings announcements are unlikely driven by exposures to omitted risk factors (La Porta et al., 1997).

We conduct independent double sorts of all of the stocks at the end of each June based on the anomaly signal and the level of analyst consensus recommendations. We take the intersection of the long leg (top 20%) and short leg (bottom 20%) of each anomaly portfolio with the most and least favorable terciles of recommendation levels. We then calculate the mean DGTW-adjusted CAR[0,+1] around the next four quarters' earnings announcements for each of the four portfolios.[9]

[9]Wee Daniel, Grinblatt, Titman, and Wermers (1997) for details about the construction of DGTW-adjusted CAR.

The consistent (inconsistent) group refers to the stocks where analyst recommendations are congruent with (contradictory to) the anomaly predictions.

Table 6 shows that our results also hold for earnings announcement returns. The abnormal returns to the long-short of the portfolio are larger when the analyst recommendations are contradictory to the anomaly predictions. For example, for the composite mispricing score PERF, the long-short portfolio generates a DGTW-adjusted CAR[0,+1] of 2.53% (*t*-stat = 17.85) when the analyst recommendations are contradictory to the anomaly predictions; by contrast, it is 2.15% (*t*-stat = 15.49) when the analyst recommendations are congruent with the anomaly predictions. The difference between the two is 0.38% with a *t*-stat of 2.04 and is most pronounced in the short leg of the portfolio. In other words, the stocks in the short leg of the anomaly with favorable analyst recommendations earn particularly negative returns around earnings announcements.

[Insert Table 6 here]

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 proves to be inefficient ex post. This bias for analysts as a whole, however, may mask the great heterogeneity among individual analysts who differ significantly in their skills and incentives to generate informative recommendations. To shed further light on this issue, for each analyst, we calculate the correlation between her recommendation values and the two composite mispricing scores among all of the stocks covered by the analyst during the past three years. As anomaly signals contain expected return information, skilled or unbiased analysts' recommendations should be more closely aligned with the anomaly signals on average. Using this correlation measure as a proxy for analyst skill, we further study which analysts tend to issue recommendations that are more consistent with anomaly predictions. Specifically, we run the following panel regression:

$$Corr_s = \alpha + \beta_1 AllStar + \beta_2 Away\ from\ consensus + \beta_3 Accuracy + \beta_4 FirmExp + \beta_5 TotalExp + \beta_6 \ln(BrokerSize) + \beta_7 PortfolioSize + \beta_8 Coverage + \epsilon_{i,t+1}, \quad (3)$$

where $s \in \{MGMT, PERF\}$ and $Corr_s$ stands for the correlation between analyst recommendation values and composite mispricing scores MGMT (or PERF). $AllStar$ is a dummy variable that equals one if the analyst is ranked as an All-American analyst. $Away\ from\ consensus$ is a dummy variable that equals one if analyst i's absolute deviation in recommendation change from the consensus is larger than her prior deviation. $Accuracy$ is the difference between the absolute forecast error of analyst i's forecast and the average absolute forecast error across all analysts' forecasts. $FirmExp$ is the number of years an analyst has covered the firm. $TotalExp$ is the number of years 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 employing the analyst. $Coverage$ is the total number of firms followed by the analyst. We also control for analyst and year fixed effects in some specifications.

Table 7 presents the regression results. Across different specifications, forecast accuracy is positively related to our correlation measure and is particularly strong for $Corr_{PERF}$. $Corr_{PERF}$ is also positively related to the analyst's total working experience and the size of the brokerage firm, suggesting analysts with longer working experience and in larger brokerage firms are more likely to use performance-related anomaly information. However, for $Corr_{MGMT}$, we find the opposite results. Large brokerage firm size and longer working experience are negatively related to $Corr_{MGMT}$, suggesting analysts' biased recommendations for MGMT-related anomalies may be due to strategic reasons.

[Insert Table 7 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 measure, controlling for recommendation, analyst, broker, and firm characteristics shown by the literature that affect the informativeness of analyst recommendations. Specifically, we run the following panel regression:

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

where Y_i is the two-day cumulative abnormal returns ($CAR[0,+1]$) or the two-day absolute cumulative abnormal return ($|CAR[0,+1]|$) around analyst recommendations. $Corr_s$ is the correlation of analyst recommendation with the composite mispricing measure, MGMT or PERF. $|\Delta Rec_{individual}|$ is the absolute value of the recommendation change of an individual analyst. Other variables are as defined previously. $X_{k,i,t}$ stands for the vector of firm characteristics, including$Ln(Size)$, $Rank_{BV}$, $Volatility$, $MOM_{(-21,-1)}$, and $MOM_{(-252,-22)}$.

Table 8 reports the regression results. The coefficient on $Corr_{PERF}$ is significantly positive for upward recommendation changes, and significantly negative for downward recommendation changes. The coefficient on $Corr_{MGMT}$ is insignificant for both upward and downward recommendation changes. The results suggest that the market perceives analysts who are better at using performance-related anomaly signals as more skilled in general, and hence these analysts elicit stronger market reactions. The economic magnitude is substantial. 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 anomaly rankings ($Corr_{PERF}$ = 1) generates a two-day announcement return 0.4% higher than analysts whose recommendations are unrelated to anomaly signals ($Corr_{PERF}$ = 0). The result is even stronger for downward recommendation changes; market reactions to downward recommendation changes of skilled analysts are 0.7% more negative than those of unskilled analysts.

The incremental effect of our measure of skilled analysts survives after controlling for firm and analyst fixed effects in the panel regression. 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 anomaly information for her recommendations.

As a robustness check, we also conduct a regression by pooling upgrades and downgrades together and multiplying downgrade $CAR[0,+1]$ by -1. Panel C presents the result, which confirms the informativeness of recommendations issued by skilled analysts whose recommendations are more aligned with anomaly signals.

5. Additional Tests and Alternative Explanations

5.1. Results in the post-publication period

One alternative 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 publication 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 9 shows the Fama–French alpha 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 MGMT-related anomalies. Out of 11 anomalies, only 6 still generate significantly positive alphas (based on a one-sided test with t-stat > 1.65), whereas three (all from PERF) actually generate negative alphas, with GP earning a significantly negative alpha of -0.44% (t-stat = -1.78). Panel B reports the mean recommendation levels and changes for quintile portfolios sorted on each anomaly in the post-publication period. The result shows that for all MGMT-related anomalies, analysts still assign more favorable recommendations 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 analysts' unawareness of the return predictability of the anomalies does not fully explain our findings.

[Insert Table 9 here]

5.2. Effect of firm size

A typical explanation for why well-documented anomalies are not arbitraged away is limits to arbitrage. 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 may be a source of frictions that impede 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 limits-to-arbitrage explanation, we redo our main tests for small and big firms separately. If the preceding 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 in the bottom (top) 30% using the NYSE size breakpoints as cutoffs.

Panel A of Table 10 reports analyst recommendations across quintile portfolios sorted on 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 0.56 higher recommendation value to the short leg of MGMT than to the long leg among small stocks. For big stocks, this number is 0.55 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 10 here]

Panel B of Table 10 shows that the degree to which biased analyst recommendations amplify anomaly returns does not differ significantly across small and big stocks. Take the composite mispricing measure PERF as an example. The difference in the monthly alphas between consistent and inconsistent L/S portfolios is 0.74% (*t*-stat = 2.95) for small stocks and 0.60% (*t*-stat = 2.68) for big stocks. Overall, our results do not 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 may be a noisy proxy for trading frictions, we redo the subsample tests based on trading cost measures, where the trading cost is measured as the daily percentage quoted spread following Chung and Zhang (2014). The results are quite similar, as reported in Table A1 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 documented that institutional investors as a group tend to trade in opposition to the prescriptions of stock return anomalies. For example, institutions tend to buy growth stocks and sell value stocks (Frazzini and Lamont, 2008; Jiang, 2010). Edelen, Ince, and Kadlec (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 sub-samples divided by stocks' institutional ownership. Analysts' recommendations should be more biased for stocks held by more institutions according to this alternative explanation.

Panel A of Table 11 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 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 is 0.56 higher than those for the long leg of MGMT. The difference in recommendations between two extreme quintiles is 0.54 among stocks with low institutional ownership.

[Insert Table 11 here.]

Panel B of Table 11 further shows that analysts' biased recommendations amplify anomaly returns to a similar degree for stocks with low and high institutional ownership. Take the PERF composite mispricing measure as an example. The difference in L/S portfolio alphas between consistent and inconsistent groups is 0.63% (*t*-stat = 2.14) for stocks with low institutional ownership and 0.55% (*t*-stat = 2.45) for stocks with high institutional ownership. Overall, the evidence is inconsistent with the alternative explanation that analysts issue biased recommendations mainly to cater to institutional investors' preferences.

In Table A2 in the Online Appendix, we conduct a similar subsample test based on the stock's ownership by long-horizon institutional investors, who are defined as those "dedicated" 13F institutions following the classification of Bushee (1998).[10] 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 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 that the amplification effect of analysts' biased recommendations on anomaly returns

[10] According to Bushee (2001), dedicated institutions are characterized by large average investments in portfolio firms and extremely low turnover, consistent with a "relationship investing" role and a commitment to provide long-term patient capital.

should be more pronounced during high- rather than low-sentiment periods. To test this conjecture, we use the Baker and Wurgler (2006) Sentiment Index as a proxy for the aggregate investor sentiment in the stock market and 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 a low-sentiment period otherwise. We then evaluate how analysts differentially use anomaly information over high- and low-sentiment periods.

Panel A of Table 12 reports the mean 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 long- and short legs of MGMT is -0.29. Following high-sentiment periods, the difference in recommendation values between the long- and short legs of MGMT increases to -0.60. Given the evidence that anomalies have stronger return predictability in high-sentiment periods (Stambaugh et al., 2012), analysts should follow anomalies more closely in 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 12 shows not only that analyst recommendations are more biased during the high-sentiment periods, but also that their biased recommendations amplify anomaly returns more strongly in such times. Take the PERF composite mispricing measure as an example. The difference in the L/S portfolio alphas between consistent and inconsistent groups is an insignificant 0.12% during low-sentiment periods, while it is 0.99% (*t*-stat = 3.30) during high-sentiment periods. Overall, the subsample results based on the Sentiment Index suggests that behavioral bias on the part of analysts is partially responsible for analysts' inefficient use of anomaly information.

5.5. Other anomalies

So far, we have focused on the 11 prominent anomalies proposed by Stambaugh et al. (2012) to avoid cherry-picking the anomalies. In this section, we examine whether our main results hold for six other prominent anomalies, including idiosyncratic volatility (IVOL) (Ang, Xing, and Zhang, 2006), maximum daily returns in the last month (MaxReturn) (Bali, Cakici, and Whitelaw, 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 (Baker, Bradley, and Wurgler, 2011; Frazzini and Pedersen 2014). These anomalies are also documented to be associated with significant abnormal returns by various studies.

Table A3 in the Online Appendix reports the long-short portfolio returns of these six new anomalies. Panel A reports the raw returns and Panel B reports the Fama and French (1993) three-factor adjusted alphas. Overall, all of the long-short portfolios based on these six anomalies generate significant Fama and French (1993) three-factor alphas, with monthly alphas ranging from 0.4% to 1%.

We then examine whether analysts take advantage of this anomaly information when recommending stocks. Table A4 reports the level and change of the consensus recommendations for quintile portfolios sorted on each of the six anomalies. Similar to our baseline results, our findings are pervasive across all six anomalies. Stocks in the short leg of anomalies tend to receive more favorable recommendations than do stocks in the long leg. Table A5 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 out of 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.

5.6. Informativeness of analyst consensus recommendations

Jegadeesh et al. (2004) examine the informativeness of consensus analyst recommendations using the recommendation data from Zacks Investment Research from 1985 to 1998. Similarly, Barber et al. (2001) look at the investment value of consensus recommendation using Zacks data from 1985 to 1996. Their results show that stocks with favorable (upgraded) analyst recommendations outperform stocks 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 re-examine 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 consensus recommendations (both the level and change of recommendations) observed at the end of the last quarter, and re-balance the portfolio quarterly. Panel A of Table A6 reports the 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 the portfolios monthly, with corresponding results reported in Panel B of Table A6.

Our results show that the level of recommendation is uninformative for future returns over various sample periods, while the change of recommendations is more informative. However, the economic magnitude of the return predictability of the change of recommendations is relatively small, generating an alpha of 30 bps per month over the full sample. In addition, analyst recommendations seem to be more informative in the early periods. The change of consensus recommendations generates an alpha of 69 bps over the 1993-2000 period, while the alpha becomes insignificant in the 2000-2014 period.[11] Overall, we believe 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 value and efficiency of analyst recommendations through the lens of capital market anomalies. Contrary to the common view that analysts are sophisticated information intermediaries who help improve market efficiency, we show that analysts do not fully use the information in anomaly signals when making recommendations. In particular, analysts tend to give more favorable recommendations to stocks classified as overvalued (the short leg of an anomaly), and these stocks tend to have particularly negative abnormal returns in the future. Overall, our results suggest that analysts' biased recommendations could be a source of market frictions that impede the efficient correction of mispricing.

[11] 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.

We make several contributions to the literature. First, we contribute to the literature on the origin and persistence of stock return anomalies by showing that analysts' biased recommendations can be a significant force contributing to mispricing in the financial market. Second, we contribute to our understanding of analysts' role as informational intermediaries by revealing that analysts do not use the valuable information in anomaly signals when making recommendations and often contradict anomaly prescriptions. Lastly, we develop a simple method to identify skilled unbiased analysts based on the correlation between their recommendation values and anomaly signals, and show its usefulness beyond existing analyst skills or experience measures.

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Table 1: Summary statistics

This table reports summary statistics for the main variables used in this study. Rec (ΔRec) stands for the level (change) of analyst consensus recommendations, where 5 is strong buy and 1 is strong sell. $Corr_{\mathrm{MGMT}}$ ($Corr_{\mathrm{PERF}}$) is the correlation between analyst recommendation ranking and two composite mispricing rankings, constructed following Stambaugh and Yuan (2017). $|\Delta Rec_{individual}|$ is the absolute value of the change of individual analyst's recommendation. $AllStar$ 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 in the year prior to the recommendation change 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 3 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. This figure is multiplied by (-1) and averaged across all stocks covered the analyst in a given year. A higher value of this variable indicates higher precision of the analyst's forecasts. $FirmExp$ is the number of years an analyst has covered the firm since the analyst's first forecast on this firm appears in I/B/E/S. $TotalExp$ is the number of years 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. $Rank_{\mathrm{BV}}$ is the ranking of a firm's book value, with 10 (1) as the largest (smallest), $Ln(Size)$ is the natural logarithm of firm market capitalization, $Volatility$ is the standard deviation of daily returns over the 63 days prior to the recommendation change, $MOM_{(-21,-1)}$ is the stock return over the 21 trading days prior to the recommendation. $MOM_{(-252,-22)}$ is the stock return over the 252 trading days prior to the recommendation, excluding the 21 trading days prior to the recommendation. The sample period is from January 1993 to December 2014.

Variable	N	Mean	Std dev	Min	p25	p50	p75	Max
Rec	380,115	3.76	0.74	1	3	4	4	5
ΔRec	314,361	-0.08	0.76	-4	-0.5	0	0.17	4
$Corr_{\mathrm{MGMT}}$	562,391	-0.04	0.26	-1	-0.19	-0.03	0.11	1
$Corr_{\mathrm{PERF}}$	547,000	0.04	0.26	-1	-0.11	0.04	0.19	1
$\lvert\Delta Rec_{individual}\rvert$	383,782	1.06	0.74	0	1	1	2	4
$AllStar$	574,954	0.09	0.29	0	0	0	0	1
$Concurrent\ Rec$	574,954	0.14	0.35	0	0	0	0	1
Pre-earnings	574,954	0.05	0.21	0	0	0	0	1
Post-earnings	574,954	0.07	0.26	0	0	0	0	1
$Away\ from\ consensus$	574,954	0.21	0.41	0	0	0	0	1
$Accuracy$	540,404	0.26	0.63	-75.91	0.14	0.31	0.45	1
$FirmExp$	558,358	2.61	3.66	0	0.09	1.22	3.55	31.99
$TotalExp$	572,400	10.51	7.42	0	4.08	9.82	15.58	32.91
$\mathrm{Ln}(BrokerSize)$	574,954	5.95	1.15	0	5.21	6.14	6.82	8.14
$Rank_{\mathrm{BV}}$	574,954	5.5	2.87	1	3	5.5	8	10
$\mathrm{Ln}(Size)$	463,736	14.35	1.80	5.25	13.09	14.28	15.56	20.14
$MOM_{(-21,-1)}$	455,419	-0.43	17.66	-375.79	-7.19	0.93	8.11	205.59
$MOM_{(-252,-22)}$	429,339	0.02	0.21	-2.27	-0.07	0.04	0.13	1.67
$Volatility$	446,408	0.03	0.02	0	0.02	0.03	0.04	0.7
$Coverage$	574,954	9.57	6.54	1	5	8	13	46

Table 2: Informativeness of anomaly signals

This table reports average returns and alphas on the long-short portfolios of 11 anomalies and two composite mispricing factors. We group 11 anomalies into 2 clusters. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. Panel A (Panel B) reports the raw returns of Cluster 1 (Cluster 2) anomalies and Panel C (Panel D) the Fama-French (1993) three-factor alphas of Cluster 1 (Cluster 2) anomalies. The *t*-statistics are in parentheses. The sample period is 1993-2014.

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%
	(4.16)	(4.31)	(4.71)	(3.01)	(3.49)	(3.46)	(3.33)
Short	0.53%	0.67%	0.76%	0.78%	0.57%	0.50%	0.59%
	(1.24)	(1.62)	(1.83)	(1.78)	(1.50)	(1.15)	(1.41)
Long – Short	0.72%	0.57%	0.44%	0.35%	0.62%	0.76%	0.60%
	(3.12)	(2.63)	(1.73)	(2.08)	(3.65)	(3.89)	(3.60)
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%	
	(3.96)	(4.45)	(3.15)	(3.27)	(3.75)	(3.81)	
Short	0.58%	0.81%	0.88%	0.62%	0.83%	0.51%	
	(1.41)	(2.23)	(1.97)	(1.40)	(2.58)	(1.01)	
Long – Short	0.75%	0.48%	0.27%	0.66%	0.50%	0.82%	
	(3.68)	(2.63)	(1.51)	(2.10)	(2.93)	(3.23)	
Panel C: Cluster 1 (Alphas)							
	MGMT	NSI	CEI	Accrual	NOA	TAG	IA
Long	0.23%	0.26%	0.32%	0.00%	0.17%	0.13%	0.07%
	(3.61)	(3.22)	(3.82)	(-0.01)	(1.84)	(1.84)	(0.86)
Short	-0.62%	-0.48%	-0.37%	-0.35%	-0.55%	-0.63%	-0.57%
	(-4.83)	(-4.88)	(-3.02)	(-2.93)	(-4.43)	(-4.84)	(-4.19)
Long – Short	0.86%	0.75%	0.68%	0.35%	0.72%	0.76%	0.64%
	(5.75)	(6.53)	(5.09)	(2.75)	(4.28)	(5.11)	(4.38)
Panel D: Cluster 2 (Alphas)							
	PERF	Distress	O-score	MOM	GP	ROA	
Long	0.36%	0.37%	0.13%	0.24%	0.29%	0.32%	
	(3.85)	(3.65)	(1.33)	(1.87)	(3.04)	(3.22)	
Short	-0.63%	-0.33%	-0.31%	-0.62%	-0.18%	-0.77%	
	(-4.72)	(-2.56)	(-2.91)	(-3.02)	(-1.50)	(-5.37)	
Long – Short	0.99%	0.69%	0.45%	0.86%	0.47%	1.09%	
	(5.34)	(4.03)	(3.15)	(2.85)	(2.95)	(5.64)	

Table 3: Analyst consensus recommendations for anomaly stocks

This table reports the average level and change of consensus recommendations for quintile portfolios sorted by the anomaly variables. We classify anomalies into 2 clusters. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

Panel A: Cluster 1								
	MGMT		NSI		CEI		Accrual	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.53	-0.06	3.63	-0.08	3.55	-0.06	3.70	-0.06
2	3.64	-0.05	3.65	-0.05	3.62	-0.05	3.67	-0.05
3	3.78	-0.02	3.75	-0.03	3.79	-0.08	3.79	-0.01
4	3.92	-0.02	3.88	0.00	3.91	-0.03	3.91	0.00
Short	4.09	0.02	4.02	0.02	4.02	0.04	4.06	0.01
Long - Short	-0.56***	-0.08***	-0.39***	-0.10***	-0.48***	-0.10***	-0.36***	-0.06***
	NOA		AG		IA			
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec		
Long	3.72	-0.04	3.62	-0.06	3.69	-0.01		
2	3.72	-0.03	3.62	-0.04	3.76	-0.03		
3	3.72	-0.02	3.76	-0.04	3.79	-0.03		
4	3.79	-0.03	3.90	-0.02	3.88	-0.03		
Short	4.02	-0.03	4.07	0.00	4.02	-0.02		
Long – Short	-0.30***	-0.01	-0.46***	-0.06***	-0.33***	0.01		
Panel B: Cluster 2								
	PERF		Distress		O-score		MOM	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.91	0.04	3.84	0.01	3.89	-0.02	3.91	0.07
2	3.85	0.01	3.84	0.01	3.81	0.01	3.78	0.01
3	3.78	-0.03	3.82	-0.01	3.78	-0.01	3.74	-0.01
4	3.70	-0.07	3.73	-0.03	3.76	-0.03	3.73	-0.06
Short	3.72	-0.11	3.65	-0.09	3.86	-0.05	3.79	-0.15
Long – Short	0.19***	0.15***	0.19***	0.10***	0.03***	0.03***	0.13***	0.22***
	GP		ROA					
	Rec	ΔRec	Rec	ΔRec				
Long	3.85	-0.01	3.94	0.03				
2	3.85	-0.03	3.85	0.01				
3	3.85	-0.03	3.76	-0.03				
4	3.74	-0.03	3.64	-0.07				
Short	3.69	-0.06	3.82	-0.10				
Long – Short	0.16***	0.05***	0.12***	0.13***				

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, we sort stocks into three groups based on the level of analyst consensus recommendations, and independently into quintiles based on anomaly characteristic. 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 abnormal returns between Inconsistent and Consistent portfolios. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The *t*-statistics are shown in parentheses. The sample period is 1993-2014.

Panel A: Cluster 1

	MGMT		NSI		CEI		Accrual	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.40%	0.17%	0.37%	0.23%	0.44%	0.27%	0.10%	0.07%
	(4.04)	(2.24)	(3.73)	(2.61)	(4.13)	(2.92)	(0.89)	(0.71)
Short	-0.83%	-0.44%	-0.63%	-0.45%	-0.51%	-0.21%	-0.64%	-0.07%
	(-5.47)	(-2.99)	(-5.05)	(-3.79)	(-3.66)	(-1.70)	(-4.37)	(-0.49)
Consistent	0.85%		0.81%		0.65%		0.18%	
	(4.67)		(5.31)		(4.25)		(1.02)	
Inconsistent	1.00%		0.87%		0.77%		0.72%	
	(5.58)		(5.80)		(4.87)		(4.10)	
Diff: Incon – Con	0.16%		0.05%		0.12%		0.54%	
	(0.78)		(0.28)		(0.70)		(2.30)	

	NOA		AG		IA	
	Up	Down	Up	Down	Up	Down
Long	0.08%	0.18%	0.22%	0.06%	0.11%	0.14%
	(0.55)	(1.79)	(2.12	(0.74)	(1.08)	(1.55)
Short	-0.69%	-0.48%	-0.84%	-0.44%	-0.85%	-0.38%
	(-4.65)	(-3.87)	(-5.33)	(-3.08)	(-5.34)	(-2.65)
Consistent	0.56%		0.66%		0.48%	
	(2.84)		(3.90)		(2.86)	
Inconsistent	0.87%		0.90%		0.99%	
	(4.40)		(4.86)		(5.42)	
Diff: Incon – Con	0.31%		0.24%		0.51%	
	(1.51)		(1.18)		(2.38)	

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

Panel B: Cluster 2

	PERF		Distress		O-score		MOM	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.40%	0.47%	0.36%	0.36%	0.08%	0.22%	0.40%	0.41%
	(3.51)	(4.67)	(2.81)	(3.21)	(0.64)	(1.96)	(2.62)	(2.88)
Short	-1.09%	-0.50%	-0.71%	-0.27%	-0.55%	-0.18%	-1.09%	-0.45%
	(-5.98)	(-4.11)	-4.24	-1.85	(-3.81	-1.43)	(-4.65)	(-2.04)
Consistent	0.90%		0.63%		0.26%		0.85%	
	(4.82)		(3.08)		(1.42)		(2.54)	
Inconsistent	1.57%		1.07%		0.76%		1.50%	
	(6.54)		(5.03)		(4.24)		(4.43)	
Diff: Incon – Con	0.67%		0.44%		0.50%		0.65%	
	(3.17)		(2.27)		(2.24)		(3.40)	

	GP		ROA	
	Up	Down	Up	Down
Long	0.22%	0.37%	0.28%	0.49%
	(1.82)	(3.41)	(2.19)	(4.95)
Short	-0.39%	-0.11%	-1.07%	-0.63%
	(-2.51)	(-0.88)	(-6.20	(-4.33)
Consistent	0.33%		0.91%	
	(1.98)		(4.21)	
Inconsistent	0.76%		1.56%	
	(3.64)		(7.23)	
Diff: Incon – Con	0.43%		0.65%	
	(2.17)		(2.98)	

Table 5: Fama-MacBeth Regressions

This table reports the Fama and MacBeth (1973) regressions of stock returns on the anomaly characteristics interacted with analyst consensus recommendations. Long (short) is a dummy variable that equals one for stocks in the top (bottom) quintile based on the anomaly signal. RecUp (RecDown) is a dummy that equals one for stocks in the top (bottom) tercile based on the consensus recommendation. We run the Fama-MacBeth regression as follows:

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

where $X_{k,i,t}$ stands for a set of firm controls, including firm size, short-term reversal, book-to-market ratio, idiosyncratic volatility, past 12-month turnover, analyst forecast dispersion, and last month maximum return. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The significance of the estimates is based on Newey-West (1987) adjusted t-statistics. *, **, and *** indicate the significance levels at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1993 to December 2014.

Dependent Variable: Excess Return (%)

Panel A: Cluster 1

	MGMT	NSI	CEI	Accrual	NOA	AG	IA
$Long \times RecUp$	0.272**	0.083	0.124	0.421***	-0.144	0.241*	0.128
	(2.16)	(0.70)	(0.92)	(2.92)	(-0.81)	(1.66)	(1.04)
$Long \times RecMid$	0.340*	0.007	0.176	0.279	0.109	0.438*	0.161
	(1.68)	(0.06)	(1.27)	(1.26)	(0.64)	(1.95)	(0.67)
$Long \times RecDown$	0.295**	0.016	-0.033	0.558*	0.040	0.354**	0.583***
	(2.49)	(0.11)	(-0.20)	(1.90)	(0.23)	(2.12)	(2.87)
$Short \times RecUp$	-0.688***	-0.536***	-0.470***	-0.304*	-0.550***	-0.760***	-0.477**
	(-4.37)	(-4.89)	(-3.60)	(-1.87)	(-3.43)	(-3.93)	(-2.36)
$Short \times RecMid$	0.166	0.125	0.036	0.223	-0.224	-0.161	0.275
	(0.69)	(0.51)	(0.23)	(0.78)	(-1.60)	(-1.03)	(1.01)
$Short \times RecDown$	-0.403**	-0.571***	-0.195	-0.045	-0.409**	-0.522**	-0.389*
	(-2.16)	(-3.31)	(-0.91)	(-0.20)	(-2.54)	(-2.29)	(-1.93)
$Short\text{-}term\ reversal$	-1.484**	-1.538**	-1.464**	-1.514**	-1.511**	-1.567**	-1.639***
	(-2.33)	(-2.48)	(-2.34)	(-2.43)	(-2.42)	(-2.50)	(-2.68)
$Ln(Size)$	-0.070	-0.077	-0.073	-0.063	-0.073	-0.069	-0.055
	(-1.32)	(-1.54)	(-1.49)	(-1.18)	(-1.38)	(-1.33)	(-1.06)
$Ln(B/M)$	-0.050	-0.053	-0.046	-0.036	-0.041	-0.055	-0.040
	(-0.39)	(-0.41)	(-0.35)	(-0.28)	(-0.33)	(-0.43)	(-0.30)
$IVOL$	-9.001	-12.878	-11.743	-12.212	-10.896	-10.719	-9.256
	(-0.94)	(-1.45)	(-1.30)	(-1.29)	(-1.15)	(-1.17)	(-0.99)
$Turnover$	0.490	0.339	0.404	0.154	0.374	0.370	0.093
	(0.45)	(0.31)	(0.37)	(0.14)	(0.34)	(0.35)	(0.09)
$Dispersion$	0.000	0.062	0.111	-0.149	0.243	0.214	0.044
	(0.00)	(0.15)	(0.25)	(-0.39)	(0.60)	(0.57)	(0.11)
$MaxReturn$	-0.764	0.069	-0.641	-1.000	-0.332	-0.092	-1.102
	(-0.29)	(0.03)	(-0.24)	(-0.36)	(-0.12)	(-0.04)	(-0.43)
N	520,034	520,034	520,034	520,034	520,034	520,034	520,034
Adjusted R^2	0.072	0.072	0.071	0.074	0.074	0.074	0.075

Table 5 (continued): Fama-MacBeth Regressions

Dependent variable: Excess returns (%)						
Panel B: Cluster 2						
	PERF	Distress	O-score	MOM	GP	ROA
$Long \times RecUp$	0.281**	0.203	0.186	0.275	0.213	0.352**
	(2.42)	(1.20)	(1.46)	(1.37)	(1.50)	(2.54)
$Long \times RecMid$	0.398***	0.102	0.232	0.664***	0.606**	0.489***
	(3.13)	(0.77)	(1.36)	(3.24)	(2.18)	(3.62)
$Long \times RecDown$	0.323*	0.189	0.191	0.510**	0.511***	0.354**
	(1.96)	(1.36)	(1.40)	(2.01)	(3.65)	(2.24)
$Short \times RecUp$	-0.756***	-0.779**	-0.073	-0.591***	-0.400*	-0.921***
	(-3.19)	(-2.58)	(-0.36)	(-2.67)	(-1.83)	(-3.17)
$Short \times RecMid$	0.053	0.238	0.108	0.002	-0.080	-0.087
	(0.23)	(1.02)	(0.41)	(0.01)	(-0.42)	(-0.22)
$Short \times RecDown$	-0.437***	-0.339**	0.211	-0.169	-0.346	-0.088
	(-2.80)	(-2.15)	(1.26)	(-0.86)	(-1.43)	(-0.33)
$Short\text{-}term\ reversal$	-1.625***	-1.506**	-1.511**	-1.359**	-1.547**	-1.701***
	(-2.61)	(-2.43)	(-2.41)	(-2.15)	(-2.52)	(-2.68)
$Ln(Size)$	-0.069	-0.066	-0.066	-0.060	-0.063	-0.080
	(-1.36)	(-1.26)	(-1.27)	(-1.12)	(-1.18)	(-1.64)
$Ln(B/M)$	0.035	-0.010	-0.018	0.048	0.021	0.007
	(0.27)	(-0.08)	(-0.14)	(0.42)	(0.16)	(0.05)
$IVOL$	-12.760	-14.032	-14.855	-13.182	-13.927	-11.836
	(-1.38)	(-1.54)	(-1.58)	(-1.50)	(-1.54)	(-1.21)
$Turnover$	-0.053	0.004	0.075	-0.048	-0.121	0.140
	(-0.05)	(0.00)	(0.07)	(-0.05)	(-0.11)	(0.13)
$Dispersion$	0.277	0.414	0.168	0.302	0.314	0.385
	(0.70)	(0.97)	(0.40)	(0.78)	(0.81)	(0.96)
$MaxReturn$	0.363	0.010	0.162	-0.172	-0.198	0.369
	(0.14)	(0.00)	(0.06)	(-0.07)	(-0.08)	(0.14)
N	520,034	520,034	520,034	520,034	520,034	520,034
Adjusted R^2	0.075	0.070	0.073	0.078	0.077	0.078

Table 6: Earnings announcement returns

This table reports the two-day cumulative abnormal return (CAR [0, +1]) around quarterly earnings announcements 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 anomaly characteristics. 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 CAR [0, +1] between the Inconsistent and Consistent portfolios. Panel A (Panel B) reports the results of Cluster 1 (Cluster 2) anomalies. The *t*-statistics are shown in parentheses. The sample period is 1993-2014.

Panel A: Cluster 1								
	MGMT		NSI		CEI		Accrual	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.11%	0.10%	0.18%	0.15%	0.29%	0.19%	-0.16%	0.12%
	(1.06)	(1.05)	(1.64)	(2.03)	(3.40)	(2.73)	(-1.33)	(1.17)
Short	0.12%	0.00%	-0.09%	0.00%	0.17%	0.20%	0.14%	0.22%
	(1.30)	(0.03)	(-0.98)	(-0.03)	(2.13)	(1.69)	(1.37)	(1.50)
Consistent	0.11%		0.19%		0.09%		-0.38%	
	(0.48)		(0.87)		(0.57)		(-1.88)	
Inconsistent	-0.03%		0.24%		0.02%		-0.02%	
	-(0.19)		(1.65)		(0.12)		(-0.12)	
Diff: Incon – Con	-0.14%		0.06%		-0.08%		0.36%	
	(-0.61)		(0.26)		(-0.43)		(1.78)	
	NOA		AG		IA			
	Up	Down	Up	Down	Up	Down		
Long	-0.10%	0.09%	-0.24%	0.10%	-0.07%	0.22%		
	(-1.13)	(0.95)	(-2.65	1.11	(-0.61)	2.24		
Short	0.12%	-0.06%	0.04%	-0.05%	-0.03%	-0.07%		
	(0.98)	(-0.62)	(0.37)	-0.29	(-0.27)	-0.73		
Consistent	-0.04%		-0.20%		0.00%			
	(-0.26)		(-1.13)		(-0.03)			
Inconsistent	-0.03%		0.06%		0.25%			
	(-0.15)		(0.38)		(1.70)			
Diff: Incon – Con	0.01%		0.25%		0.25%			
	(0.09)		(1.49)		(1.21)			

Table 6 (continued): Earnings announcement returns

Panel B: Cluster 2

	PERF		Distress		O-score		MOM	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	1.38%	1.45%	0.89%	0.90%	0.26%	0.20%	1.78%	1.84%
	(13.30)	(10.93)	(10.45)	(10.88)	(2.28)	(1.96)	(13.08)	(16.29)
Short	-1.08%	-0.77%	-0.61%	-0.19%	-0.39%	0.07%	-1.73%	-1.45%
	(-16.19)	(-8.12)	(-7.14)	(-3.01)	(-4.46)	(0.57)	(-23.14)	(-11.10)
Consistent	2.15%		1.08%		0.19%		3.23%	
	(15.49)		(9.39)		(1.08)		(15.46)	
Inconsistent	2.53%		1.52%		0.59%		3.57%	
	(17.85)		(11.50)		(4.06)		(23.15)	
Diff: Incon – Con	0.38%		0.44%		0.40%		0.34%	
	(2.04)		(3.15)		(1.83)		(1.89)	

	GP		ROA	
	Up	Down	Up	Down
Long	0.38%	0.50%	0.94%	0.98%
	(6.27)	(4.66)	(8.86)	(7.91)
Short	-0.27%	-0.03%	-1.04%	-0.86%
	(-3.96)	(-0.40)	(-12.57)	(-8.18)
Consistent	0.42%		1.79%	
	(3.83)		(10.91)	
Inconsistent	0.77%		2.03%	
	(5.74)		(11.27)	
Diff: Incon – Con	0.35%		0.23%	
	(1.82)		(0.81)	

Table 7: Determinants of analyst skills

This table presents panel regression results of analyst skills on analyst and firm characteristics, where skill is measured as the correlation between individual analyst' recommendations and two mispricing scores among stocks covered by the analyst. We conduct the panel regression as follows:

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

where $Corr_s$ stands for the correlation between individual analyst' recommendations and two mispricing scores, MGMT or PERF, among all stocks covered by the analyst. All other variables are defined in Table 1. Standard errors are clustered by analyst, and t-statistics are reported in parentheses. *, **, and *** indicate the significance levels at the 10%, 5%, and 1% levels, respectively. The sample period is from 1993 to 2014.

	$Corr_{MGMT}$				$Corr_{PERF}$			
$AllStar$	-0.004	-0.014**	-0.003	-0.011*	0.007	0.012**	0.006	0.012*
	(-0.74)	(-2.21)	(-0.56)	(-1.75)	(1.43)	(2.00)	(1.21)	(1.85)
$Away\ from\ consensus$	-0.001	-0.000	-0.001	-0.001	-0.001	-0.004	-0.001	-0.003
	(-0.25)	(-0.03)	(-0.41)	(-0.30)	(-0.39)	(-1.14)	(-0.17)	(-1.00)
$Accuracy$	0.004**	0.002	0.005**	0.002	0.006***	0.005**	0.005***	0.005**
	(2.10)	(0.63)	(2.21)	(0.75)	(3.01)	(2.42)	(2.78)	(2.14)
$FirmExp$	-0.000	-0.001	-0.000	-0.001	-0.001*	-0.001**	-0.001*	-0.001*
	(-1.06)	(-1.49)	(-0.97)	(-1.47)	(-1.95)	(-2.17)	(-1.66)	(-1.68)
$TotalExp$	-0.000*	-0.000	-0.000**	-0.001**	0.001***	-0.000	0.001***	0.001**
	(-1.78)	(-0.55)	(-2.20)	(-1.99)	(2.73)	(-0.02)	(3.65)	(2.55)
$Ln(BrokerSize)$	-0.008***	-0.007***	-0.008***	-0.007***	0.004***	0.002	0.004***	0.002
	(-5.45)	(-3.81)	(-5.26)	(-3.69)	(3.13)	(1.18)	(2.74)	(1.21)
$Coverage$	-0.000	-0.000**	-0.000	-0.000**	0.000	0.000*	0.000	0.000
	(-0.75)	(-2.30)	(-0.63)	(-2.37)	(1.56)	(1.66)	(0.94)	(1.45)
$Average\ Size$	0.000**	0.000*	0.000**	0.000	0.000	-0.000	0.000	0.000
	(2.45)	(1.74)	(2.13)	(1.29)	(0.16)	(-0.46)	(0.77)	(0.05)
Intercept	0.018**	0.013	0.017*	-0.021	0.003	0.022*	0.004	0.049***
	(2.05)	(1.17)	(1.88)	(-1.43)	(0.33)	(1.93)	(0.41)	(3.45)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Analyst FE	No	No	Yes	Yes	No	No	Yes	Yes
N	34,866	34,866	34,866	34,866	33,705	33,705	33,705	33,705
Adjusted R^2	0.0020	0.0016	0.0018	0.0042	0.0010	0.0005	0.0009	0.0055

Table 8: Market reactions to skilled analysts' recommendation announcements

This table presents the panel regression of analyst recommendation announcement returns on our measure of analyst skill, where skill is measured as the correlation between individual analyst' recommendations and two mispricing scores among stocks covered by the analyst. We estimate the panel regression as follows:

$$\begin{aligned} Y_i = {} & \alpha + \beta_1 Corr_s + \beta_2 |\Delta Rec_{individual}| + \beta_3 AllStar + \beta_4 Concurrent\ Rec \\ & + \beta_5 Pre\text{-}earnings + \beta_6 Post\text{-}arnings + \beta_7 Away\ from\ consensus + \beta_8 Accuracy \\ & + \beta_9 FirmExp + \beta_{10} TotalExp + \sum \beta_k X_{k,i,t} + \epsilon_{i,t+1}, \end{aligned}$$

where Y_i is the 2-day cumulative abnormal return ($CAR[0,+1]$) or the 2-day absolute cumulative abnormal return ($|CAR[0,+1]|$) around recommendation announcements. $Corr_s$ is the correlation between individual analyst' recommendations and two composite mispricing scores, MGMT or PERF, among stocks covered by the analyst. All other variables are defined in Table 1. $X_{k,i,t}$ stands for the vector of firm characteristics, including $Ln(Size)$, $Rank_{BV}$, volatility, $MOM_{(-21,-1)}$, and $MOM_{(-252,-22)}$. Panel A reports the results for upgrade recommendation changes, and Panel B for downgrade recommendation changes. Panel C pools together upgrade and downgrade recommendation changes, and uses the absolute value of cumulative abnormal return ($|CAR[0,+1]|$) as the dependent variable. Standard errors are clustered at the analyst level, and *t*-statistics are reported in parentheses. *, **, and *** indicate the significance levels at the 10%, 5%, and 1% levels, respectively. The sample period is 1993-2014.

Table 8 (continued): Market reactions to skilled analysts' recommendation announcements

Panel A: Upgrade recommendation changes ($CAR[0,+1]$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	-0.000	0.001	-0.001			
	(-0.43)	(0.42)	(-0.58)			
$Corr_{PERF}$				0.002**	0.003**	0.004**
				(2.24)	(1.97)	(2.07)
$\lvert\Delta Rec_{individual}\rvert$	0.004***	0.005***	0.005***	0.004***	0.005***	0.005***
	(8.14)	(8.66)	(6.51)	(8.26)	(8.80)	(6.65)
$AllStar$	0.006***	0.003***	0.002*	0.006***	0.003***	0.003**
	(8.73)	(2.88)	(1.65)	(8.75)	(3.04)	(2.17)
$Concurrent\ Rec$	0.014***	0.013***	0.014***	0.014***	0.014***	0.014***
	(28.77)	(26.26)	(18.49)	(28.61)	(26.06)	(17.89)
$Pre\text{-}earnings$	0.004***	0.004***	0.005***	0.004***	0.003***	0.005***
	(4.12)	(3.38)	(2.94)	(3.77)	(2.97)	(2.87)
$Post\text{-}earnings$	0.002***	0.003***	0.003***	0.003***	0.004***	0.004***
	(2.85)	(4.06)	(2.63)	(3.05)	(4.32)	(2.79)
$Away\ from\ consensus$	0.002***	0.001***	0.002**	0.001***	0.001*	0.002**
	(3.51)	(2.65)	(2.32)	(3.11)	(1.96)	(2.18)
$Accuracy$	0.001	-0.000	0.001	0.001	-0.000	0.000
	(1.52)	(-0.29)	(0.65)	(1.46)	(-0.45)	(0.09)
$FirmExp$	0.000**	-0.000	0.000	0.000*	-0.000	0.000
	(2.08)	(-0.30)	(0.17)	(1.86)	(-0.75)	(0.19)
$TotalExp$	0.000***	0.004***	0.003	0.000***	0.004***	0.003
	(3.26)	(4.24)	(1.45)	(3.72)	(4.23)	(1.34)
$Ln(BrokerSize)$	0.003***	0.001***	0.002***	0.003***	0.001***	0.002**
	(15.36)	(3.47)	(2.72)	(15.02)	(3.18)	(2.37)
$Coverage$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-7.57)	(-12.57)	(-5.17)	(-7.44)	(-12.40)	(-5.16)
Intercept	-0.036***	-0.025***	(0.02)	-0.035***	-0.024***	(0.02)
	(-7.75)	(-4.78)	(-1.49)	(-7.88)	(-4.53)	(-1.20)
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
N	84,322	84,322	84,322	81,942	81,942	81,942
Adjusted R^2	0.046	0.051	0.041	0.044	0.049	0.038

Table 8 (continued): Market reactions to skilled analysts' recommendation announcements

Panel B: Downgrade recommendation changes ($CAR[0,+1]$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	-0.000	-0.001	-0.001			
	(-0.27)	(-0.38)	(-0.52)			
$Corr_{PERF}$				-0.005***	-0.006***	-0.007***
				(-3.57)	(-2.92)	(-2.71)
$\|\Delta Rec_{individual}\|$	-0.008***	-0.013***	-0.013***	-0.008***	-0.013***	-0.013***
	(-12.31)	(-13.96)	(-10.11)	(-12.44)	(-13.78)	(-10.21)
$AllStar$	-0.008***	-0.003**	-0.002	-0.007***	-0.003*	-0.001
	(-7.47)	(-2.02)	(-0.73)	(-7.14)	(-1.70)	(-0.56)
$Concurrent\ Rec$	-0.038***	-0.038***	-0.035***	-0.039***	-0.038***	-0.035***
	(-46.54)	(-43.21)	(-28.85)	(-46.69)	(-43.30)	(-29.02)
$Pre\text{-}earnings$	-0.002	0.001	0.001	-0.002	-0.000	0.001
	(-1.14)	(0.41)	(0.69)	(-1.50)	(-0.15)	(0.48)
$Post\text{-}earnings$	-0.011***	-0.009***	-0.009***	-0.011***	-0.010***	-0.009***
	(-9.93)	(-7.72)	(-5.55)	(-9.90)	(-7.90)	(-5.20)
$Away\ from\ consensus$	0.002***	0.001*	0.002*	0.002***	0.002**	0.002
	(3.24)	(1.85)	(1.87)	(3.34)	(2.15)	(1.64)
$Accuracy$	-0.001	-0.001	0.000	-0.001**	-0.001	-0.001
	(-1.61)	(-0.83)	(0.25)	(-1.99)	(-0.93)	(-0.86)
$FirmExp$	-0.000***	-0.000	-0.009***	-0.000***	-0.000	-0.011**
	(-2.94)	(-0.48)	(-2.95)	(-2.85)	(-0.51)	(-2.55)
$TotalExp$	-0.000***	0.009***	0.017***	-0.000***	0.008***	0.018***
	(-3.12)	(-7.64)	(4.76)	(-2.88)	(6.99)	(3.96)
$Ln(BrokerSize)$	-0.005***	-0.002***	-0.000	-0.005***	-0.002***	-0.000
	(-15.72)	(-3.20)	(-0.27)	(-15.52)	(-3.03)	(-0.01)
$Coverage$	-0.001***	-0.000***	-0.001***	-0.001***	-0.000***	-0.001***
	(-12.87)	(-2.62)	(-6.90)	(-12.40)	(-2.74)	(-6.65)
Intercept	0.113***	0.103***	0.023	0.117***	0.104***	0.014
	(12.41)	(9.78)	(0.87)	(12.48)	(9.63)	(0.40)
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
N	99,191	99,191	99,191	96,571	96,571	96,571
Adjust R^2	0.168	0.212	0.165	0.168	0.210	0.162

Table 8 (continued): Market reactions to skilled analysts' recommendation announcements

Panel C: Pooling upgrade and downgrade recommendation together ($\lvert CAR[0,+1]\rvert$)						
	Cluster 1			Cluster 2		
$Corr_{MGMT}$	0.001	0.001	0.001			
	(1.44)	(1.22)	(0.94)			
$Corr_{PERF}$				0.002***	0.002***	0.002*
				(2.75)	(2.75)	(1.86)
$\lvert \Delta Rec_{individual} \rvert$	0.007***	0.009***	0.009***	0.007***	0.009***	0.009***
	(35.91)	(36.54)	(31.28)	(35.30)	(36.01)	(30.75)
$AllStar$	0.004***	0.001**	0.001	0.004***	0.002**	0.001*
	(8.67)	(2.17)	(1.26)	(8.70)	(2.35)	(1.81)
$Concurrent\ Rec$	0.020***	0.019***	0.018***	0.020***	0.019***	0.019***
	(48.33)	(44.05)	(37.80)	(48.36)	(44.23)	(37.85)
$Pre\text{-}earnings$	0.004***	0.005***	0.005***	0.005***	0.005***	0.005***
	(7.12)	(6.63)	(5.97)	(7.03)	(6.49)	(6.00)
$Post\text{-}earnings$	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(13.62)	(13.06)	(12.00)	(13.86)	(13.17)	(11.96)
$Away\ from\ consensus$	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.001***
	(-4.81)	(-4.74)	(-4.02)	(-5.24)	(-5.19)	(-4.15)
$Accuracy$	0.001**	0.000	-0.000	0.001**	0.000	0.000
	(2.00)	(0.39)	(-0.10)	(2.15)	(0.48)	(0.03)
$FirmExp$	0.000***	0.000	0.003**	0.000***	-0.000	0.004***
	(2.95)	(0.04)	(2.37)	(2.65)	(-0.09)	(2.59)
$TotalExp$	0.000*	0.002***	-0.001	0.000*	0.002***	-0.001
	(1.93)	(3.24)	(-0.52)	(1.87)	(3.66)	(-0.96)
$Ln(BrokerSize)$	0.002***	-0.000	-0.001**	0.002***	-0.000	-0.001**
	(16.31)	(-0.14)	(-2.08)	(15.91)	(-0.28)	(-2.48)
$Coverage$	0.001***	0.000	0.001***	0.001***	0.000	0.001***
	(12.46)	(0.37)	(9.07)	(12.09)	(0.66)	(8.56)
Intercept	-0.061***	-0.050***	-0.023**	-0.061***	-0.051***	-0.017
	(-16.21)	(-11.02)	(-2.17)	(-16.40)	(-11.17)	(-1.47)
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
N	235,422	235,422	235,422	229,131	229,131	229,131
Adjusted R^2	0.205	0.251	0.188	0.204	0.250	0.186

Table 9: Subsample tests in post-publication periods

Panel A reports Fama-French three-factors adjusted returns for quintile portfolios sorted by 11 anomalies. Panel B reports the average level and change of analyst consensus recommendations across quintile portfolios. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. We use the post publication periods for the test. ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively.

Panel A: Alpha						
	NSI	CEI	Accrual	NOA	AG	IA
Long	0.26%	0.10%	0.03%	-0.08%	0.16%	-0.01%
	(3.20)	(1.00)	(0.29)	(-0.56)	(1.66)	(-0.11)
Short	-0.49%	-0.27%	-0.33%	-0.22%	-0.20%	-0.30%
	(-4.89)	(-2.12)	(-2.49)	(-1.79)	(-1.31)	(-1.89)
Long – Short	0.75%	0.37%	0.36%	0.14%	0.36%	0.29%
	(6.53)	(2.28)	(2.56)	(0.67)	(1.97)	(1.64)
	Distress	O-score	MOM	GP	ROA	
Long	0.09%	-0.03%	0.24%	0.16%	-0.02%	
	(0.93)	(-0.29)	(1.86)	(1.02)	(-0.28)	
Short	0.20%	0.16%	-0.62%	0.60%	-0.38%	
	(1.36)	(1.07)	(-3.02)	(3.30)	(-2.17)	
Long – Short	-0.11%	-0.20%	0.86%	-0.44%	0.35%	
	(-0.57)	(-0.94)	(2.85)	(-1.78)	(1.91)	

Table 9 (continued): Subsample tests in post-publication periods

Panel B: Single sort (Rec or ΔRec)

	NSI		CEI		Accrual		NOA	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.63	-0.08	3.48	-0.05	3.70	-0.05	3.59	0.00
2	3.65	-0.05	3.51	-0.02	3.68	-0.05	3.59	-0.01
3	3.75	-0.04	3.63	-0.03	3.79	-0.02	3.63	0.00
4	3.88	-0.01	3.76	0.00	3.90	-0.02	3.65	-0.02
Short	4.02	0.00	3.84	0.03	4.05	-0.01	3.84	0.00
Long - Short	-0.39***	-0.08***	-0.36***	-0.07***	-0.35***	-0.03***	-0.25***	0.00

	AG		IA	
	Rec	ΔRec	Rec	ΔRec
Long	3.58	-0.02	3.60	0.01
2	3.57	0.01	3.67	-0.01
3	3.63	-0.01	3.68	-0.01
4	3.74	0.01	3.72	0.00
Short	3.91	0.02	3.83	-0.01
Long – Short	-0.33***	-0.04***	-0.23***	0.03***

	Distress		O-score		MOM		GP	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.70	0.00	3.72	0.00	3.91	0.06	3.72	-0.03
2	3.73	0.00	3.72	0.01	3.78	0.00	3.79	-0.03
3	3.73	0.02	3.70	0.00	3.74	-0.02	3.78	-0.01
4	3.65	0.01	3.72	-0.01	3.73	-0.06	3.69	-0.02
Short	3.53	-0.01	3.81	0.00	3.79	-0.16	3.62	-0.01
Long – Short	0.17***	0.01	-0.10***	0.00	0.13***	0.22***	0.10***	-0.02

	ROA	
	Rec	ΔRec
Long	3.72	0.00
2	3.72	0.01
3	3.64	0.00
4	3.53	-0.01
Short	3.73	-0.03
Long – Short	-0.01	0.03***

Table 10: Subsample tests based on firm size

Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two mispricing factors. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. 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 abnormal returns between Inconsistent and Consistent portfolios. We use NYSE size breakpoints (30%) to classify stocks into small and big stocks. ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

	Small Stocks				Big Stocks			
Panel A: Single sort (Rec or ΔRec)								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.60	-0.08	4.05	0.06	3.48	-0.06	3.85	0.03
2	3.71	-0.07	3.94	-0.02	3.58	-0.03	3.78	0.01
3	3.86	-0.04	3.81	-0.06	3.71	-0.01	3.72	0.00
4	3.98	-0.04	3.73	-0.10	3.85	0.00	3.65	-0.03
Short	4.15	0.00	3.76	-0.14	4.02	0.04	3.64	-0.07
Long – Short	-0.56***	-0.07***	0.29***	0.20***	-0.55***	-0.09***	0.20***	0.11***
Panel B: Double sorts								
	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%
	(3.56)	(2.46)	(4.24)	(4.82)	(1.60)	(0.89)	(2.07)	(3.47)
Short	-0.86%	-0.51%	-1.29%	-0.61%	-0.71%	-0.31%	-0.82%	-0.36%
	(-4.82)	(-2.24)	(-5.64)	(-3.82)	(-4.40)	(-1.87)	(-4.54)	(-3.07)
Consistent	1.03%		1.22%		0.48%		0.63%	
	(4.12)		(5.90)		(2.50)		(3.17)	
Inconsistent	1.10%		1.96%		0.80%		1.23%	
	(5.35)		(7.50)		(4.15)		(4.82)	
Diff: Incon – Con	0.07%		0.74%		0.32%		0.60%	
	(0.29)		(2.95)		(1.33)		(2.68)	

Table 11: Subsample tests based on institutional ownership

Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two mispricing factors. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. 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 abnormal returns between Inconsistent and Consistent portfolios. We divide stocks into high and low institutional holdings each month according to the median institutional ownership (IOR) in the last quarter. ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

	Low Institutional Ownership				High Institutional Ownership			
Panel A: Single sort (Rec or ΔRec)								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.51	-0.09	3.90	0.04	3.56	-0.05	3.92	0.04
2	3.60	-0.07	3.79	-0.02	3.67	-0.05	3.86	0.02
3	3.74	-0.03	3.69	-0.06	3.81	-0.02	3.81	-0.01
4	3.88	-0.03	3.65	-0.07	3.94	-0.01	3.76	-0.04
Short	4.05	-0.01	3.73	-0.14	4.12	0.04	3.75	-0.09
Long – Short	-0.54***	-0.07***	0.18***	0.18***	-0.56***	-0.09***	0.17***	0.13***
Panel B: Double sorts								
	MGMT		PERF		MGMT		PERF	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.55%	0.28%	0.55%	0.63%	0.27%	0.08%	0.30%	0.39%
	(3.64)	(2.43)	(4.12)	(4.59)	(2.35)	(0.75)	(2.29)	(3.46)
Short	-0.97%	-0.65%	-1.23%	-0.69%	-0.69%	-0.18%	-0.90%	-0.44%
	(-5.35)	(-2.94)	(-5.58)	(-4.07)	(-4.24)	(-1.17)	(-4.67)	(-3.09)
Consistent	1.20%		1.24%		0.45%		0.74%	
	(4.52)		(5.84)		(2.55)		(3.46)	
Inconsistent	1.25%		1.87%		0.77%		1.29%	
	(5.46)		(6.57)		(4.33)		(5.33)	
Diff: Incon – Con	0.05%		0.63%		0.32%		0.55%	
	(0.20)		(2.14)		(1.46)		(2.45)	

Table 12: Subsample tests based on sentiment

Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two mispricing factors. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. 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 abnormal returns between Inconsistent and Consistent portfolios. We use the Baker and Wurgler (2006) sentiment index to divide the entire sample into low and high sentiment periods using the sample median as the breakpoint. ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

	Low Sentiment				High Sentiment			
Panel A: Single sort (Rec or ΔRec)								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.60	-0.08	3.80	0.02	3.56	-0.06	3.98	0.05
2	3.65	-0.06	3.78	0.00	3.67	-0.05	3.89	0.01
3	3.70	0.00	3.73	-0.02	3.82	-0.04	3.81	-0.03
4	3.75	-0.01	3.65	-0.05	3.97	-0.02	3.72	-0.08
Short	3.89	0.01	3.64	-0.10	4.16	0.02	3.76	-0.12
Long – Short	-0.29***	-0.09***	0.15***	0.12***	-0.60***	-0.08***	0.22***	0.17***
Panel B: Double sorts								
	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%
	(2.52)	(1.29)	(1.80)	(2.26)	(2.67)	(0.88)	(2.68)	(3.53)
Short	-0.43%	-0.22%	-0.46%	-0.36%	-1.09%	-0.64%	-1.61%	-0.68%
	(-2.65)	(-1.17)	(-1.73)	(-2.26)	(-4.68)	(-2.8)	(-6.19)	(-3.65)
Consistent	0.56%		0.63%		1.02%		1.14%	
	(2.36)		(2.41)		(3.68)		(4.12)	
Inconsistent	0.56%		0.75%		1.19%		2.14%	
	(2.41)		(2.22)		(4.52)		(6.18)	
Diff: Incon – Con	0.00%		0.12%		0.17%		0.99%	
	(0.00)		(0.41)		(0.56)		(3.30)	

Online Appendix Tables

Table A1: Subsample tests based on trading cost (daily percentage quoted spreads)

Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two mispricing factors. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. 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 abnormal returns between Inconsistent and Consistent portfolios. We divide stocks into high and low trading cost groups each month, where trading cost is measured by the daily percentage quoted spread following Chung and Zhang (2014). ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

	High Trading Cost				Low Trading Cost			
Panel A: Single sort (Rec or ΔRec)								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.60	-0.05	4.05	0.06	3.58	-0.05	4.03	0.05
2	3.71	-0.05	3.95	-0.01	3.69	-0.05	3.92	0.00
3	3.85	-0.04	3.82	-0.05	3.83	-0.03	3.80	-0.04
4	3.98	-0.04	3.73	-0.08	3.96	-0.04	3.73	-0.07
Short	4.15	-0.01	3.77	-0.11	4.13	-0.01	3.73	-0.12
Long – Short	-0.56***	-0.04***	0.28***	0.17***	-0.55***	-0.03***	0.30***	0.17***
Panel B: Double sorts								
	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%
	(3.15)	(1.82)	(3.82)	(5.16)	(2.40)	(1.47)	(2.12)	(3.86)
Short	-0.65%	-0.61%	-1.21%	-0.77%	-0.83%	-0.44%	-0.95%	-0.37%
	(-3.57)	(-2.98)	(-5.58)	(-4.87)	(-4.78)	(-2.43)	(-4.66)	(-2.17)
Consistent	1.11%		1.35%		0.72%		0.67%	
	(4.53)		(5.89)		(3.29)		(2.71)	
Inconsistent	0.85%		1.98%		0.97%		1.38%	
	(3.99)		(7.46)		(4.76)		(5.08)	
Diff: Incon – Con	-0.26%		0.62%		0.25%		0.71%	
	(-0.94)		(2.31)		(1.03)		(2.92)	

Table A2: Subsample tests based on long-term institutional ownership

Panel A reports the average level and change of analyst consensus recommendations for quintile portfolios sorted by the two mispricing factors. MGMT (PERF) stands for the composite mispricing factor of the first (second) cluster. 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 abnormal returns between Inconsistent and Consistent portfolios. We divide stocks into high and low institutional holdings each month according to the median institutional ownership (IOR) of dedicated institutions in the last quarter following classification of Bushee (2001) and Bushee and Noe (2000). ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

	Low Institutional Ownership				High Institutional Ownership			
Panel A: Single sort (Rec or ΔRec)								
	MGMT		PERF		MGMT		PERF	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.53	-0.06	3.92	0.05	3.54	-0.07	3.90	0.03
2	3.64	-0.04	3.85	0.02	3.66	-0.06	3.85	0.00
3	3.76	-0.01	3.75	-0.02	3.79	-0.04	3.78	-0.03
4	3.91	-0.01	3.68	-0.06	3.92	-0.03	3.73	-0.06
Short	4.08	0.02	3.71	-0.10	4.10	0.02	3.73	-0.12
Long – Short	-0.56***	-0.08***	0.21***	0.15***	-0.56***	-0.09***	0.17***	0.15***
Panel B: Double sorts								
	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%
	(3.84)	(2.74)	(2.80)	(3.54)	(1.63)	(0.40)	(2.80)	(3.88)
Short	-0.96%	-0.66%	-1.11%	-0.59%	-0.73%	-0.16%	-0.98%	-0.42%
	(-5.64)	(-3.15)	(-4.91)	(-3.88)	(-4.53)	(-0.90)	(-5.06)	(-2.95)
Consistent	1.21%		0.95%		0.35%		0.77%	
	(4.49)		(4.58)		(1.70)		(3.64)	
Inconsistent	1.23%		1.53%		0.77%		1.45%	
	(5.72)		(5.49)		(4.27)		(5.73)	
Diff: Incon – Con	0.05%		0.57%		0.42%		0.67%	
	(0.08)		(2.03)		(1.82)		(2.98)	

Table A3: Informativeness of six new anomalies

This table reports average returns and alphas on the long-short portfolios of the six new anomalies, including idiosyncratic volatility (IVOL), max daily return in last month (MaxReturn), past 12-month turnover (Turnover), cash flow duration (Duration), long-run reversal (LMW), and market beta (Beta) based on the past 5-year estimation window. Panel A reports the raw returns and Panel B the Fama-French (1993) three-factor alphas. The *t*-statistics are in parentheses. The sample period is 1993-2014.

	IVOL	MaxReturn	Turnover	Duration	LMW	Beta
Panel A: Raw returns						
Long	0.94%	0.95%	1.04%	1.08%	1.39%	0.65%
	(4.06)	(4.04)	(3.64)	(2.87)	(2.76)	(2.82)
Short	0.35%	0.70%	0.59%	0.88%	0.67%	1.23%
	(0.67)	(1.11)	(1.1)	(1.41)	(1.63)	(1.92)
Long – Short	0.59%	0.25%	0.45%	0.20%	0.72%	-0.58%
	(1.42)	(0.51)	(1.29)	(0.57)	(2.47)	(-1.17)
Panel B: Alphas						
Long	0.34%	0.36%	0.37%	0.17%	0.30%	0.08%
	(3.97)	(3.62)	(2.54)	(1.04)	(1.21)	(0.80)
Short	-0.72%	-0.46%	-0.53%	-0.25%	-0.19%	-0.05%
	(-5.43)	(-1.6)	(-2.94)	(-0.87)	(-1.14)	(-0.16)
Long – Short	1.06%	0.82%	0.90%	0.42%	0.49%	0.12%
	(5.66)	(2.65)	(4.88)	(1.96)	(1.82)	(0.38)

Table A4: Analyst consensus recommendations for the six new anomalies

This table reports the average level and change of consensus recommendations for quintile portfolios sorted by the six new anomaly variables, including idiosyncratic volatility (IVOL), max daily return in last month (MaxReturn), past 12-month turnover (Turnover), cash flow duration (Duration), long-run reversal (LMW) and market beta (Beta) using the past 5-year estimation window. Column "Rec" reports the average level of consensus recommendations and Column "ΔRec" reports the average change of consensus recommendations. ***, **, and * indicate the *p*-values of 1%, 5%, and 10% or less, respectively. The sample period is 1993-2014.

	IVOL		MaxReturn		Turnover		Duration	
	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec	Rec	ΔRec
Long	3.60	-0.03	3.66	-0.04	3.69	-0.05	3.68	-0.08
2	3.74	-0.02	3.75	-0.04	3.75	-0.06	3.73	-0.06
3	3.84	-0.03	3.81	-0.04	3.75	-0.05	3.79	-0.03
4	3.90	-0.02	3.85	-0.05	3.80	-0.04	3.85	-0.01
Short	3.93	-0.05	3.81	-0.12	3.82	-0.06	3.82	-0.10
Long – Short	-0.33***	0.02***	-0.15***	0.08***	-0.13***	0.01	-0.14***	0.02***

	LMW		Beta	
	Rec	ΔRec	Rec	ΔRec
Long	3.51	-0.15	3.64	-0.06
2	3.61	-0.07	3.68	-0.04
3	3.67	-0.02	3.74	-0.04
4	3.78	0.00	3.79	-0.05
Short	4.00	0.06	3.80	-0.06
Long – Short	-0.49***	-0.20***	-0.17***	0.00

Table A5: Abnormal returns of new anomaly portfolios conditional on analyst recommendations

This table reports the monthly Fama-French three-factor alphas of portfolios sorted independently by the six new 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 anomaly characteristics, including idiosyncratic volatility (IVOL), max daily return in last month (MaxReturn), past 12-month turnover (Turnover), cash flow duration (Duration), long-run reversal (LMW) and market beta (Beta) using the past 5-year estimation window. 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 abnormal returns between Inconsistent and Consistent portfolios. The *t*-statistics are shown in parentheses. The sample period is 1993-2014.

	IVOL		MaxReturn		Turnover		Duration	
	Up	Down	Up	Down	Up	Down	Up	Down
Long	0.42%	0.35%	0.42%	0.36%	0.04%	0.39%	-0.02%	0.32%
	(3.93)	(3.91)	(3.46)	(3.82)	(0.23)	(2.94)	(-0.13)	(2.09)
Short	-0.95%	-0.45%	-0.90%	-0.08%	-0.77%	-0.47%	-0.65%	0.02%
	(-6.08)	(-2.95)	(-3.20)	(-0.24)	(-4.21)	(-1.75)	(-2.27)	(0.06)
Consistent	0.87%		0.50%		0.51%		-0.05%	
	(3.94)		(1.36)		(1.95)		(-0.15)	
Inconsistent	1.29%		1.26%		1.16%		0.97%	
	(6.56)		(4.37)		(6.20)		(4.27)	
Diff: Incon – Con	0.42%		0.76%		0.64%		1.02%	
	(2.17)		(3.29)		(2.34)		(3.68)	

	LMW		Beta	
	Up	Down	Up	Down
Long	0.23%	0.30%	0.11%	0.00%
	(0.90)	(1.09)	(0.92)	(-0.01)
Short	-0.28%	-0.12%	-0.44%	0.23%
	(-1.69)	(-0.48)	(-1.69)	(0.58)
Consistent	0.34%		-0.11%	
	(1.05)		(-0.27)	
Inconsistent	0.58%		0.44%	
	(1.98)		(1.62)	
Diff: Incon – Con	0.24%		0.55%	
	(0.86)		(2.02)	

Table A6: Unconditional Return Predictability of Consensus Analyst Recommendations

This table reports the monthly Fama-French three-factor alphas of quintile portfolios sorted on consensus analyst recommendations. At the beginning of every quarter (month), we sort stocks into quintiles based on the level or change of recommendations observed at the last quarter (month) end, and re-balance the portfolio quarterly (monthly). Panel A (B) reports the results for quarterly (monthly) re-balanced portfolios and *t*-statistics are reported for the long minus short portfolios.

Panel A: Quarterly rebalanced portfolios

	1993-2000		2000 - 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	(-1.27)	(2.17)	(-1.32)	(0.53)	(-1.47)	(-0.31)	(-1.64)	(1.76)

Panel B: Monthly rebalanced portfolios

	1993-2000		2000 - 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	(-0.34)	(2.79)	(-0.99)	(0.59)	(-1.16)	(0.67)	(-0.77)	(2.85)