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Attention and Underreaction-Related Anomalies

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Abstract. Recent studies have proposed a large set of powerful anomaly-based factors in the stock market. This study examines the role of investor inattention in the corresponding anomalies underlying these factors and other underreaction-related anomalies. Using media coverage as a proxy for investor attention, we show that the anomalies underlying many recently proposed prominent factors are much more pronounced among firms with low media coverage in portfolio-formation periods. In addition, we find many other prominent anomalies that previous literature has attributed to underreaction also tend to perform much better among firms with low media coverage. The average Fama-French five-factor alpha spread of these anomalies is about 0.97% per month among firms with low news coverage and only 0.24% per month among firms with high news coverage. Moreover, most of the alpha spread comes from the short leg of the anomalies and from the firms that are more difficult to arbitrage. Overall, our evidence indicates that investor inattention at least partially drives many of the recently proposed factors.

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1. Introduction

Many prominent anomaly-based factors are proposed by recent studies. For example, motivated by valuation theory that links profitability and investment to expected stock returns, Fama and French (2015) augment their original three-factor model with two additional factors: the robust-minus-weak factor (RMW) and the conservative-minus-aggressive factor (CMA).[1] Meanwhile, inspired by q-theory, which also links profitability and investment to expected stock returns, Hou et al. (2015) propose two conceptually similar factors: the return-on-equity factor (ROE) and the investment factor. Because the above argument does not involve irrationality and relies only on the present value relation or the firm's first-order condition, researchers tend to treat these new factors as systematic risk factors. On the other hand, motivated by behavioral theories, Stambaugh and Yuan (2017) propose two new mispricing factors, where one factor is related to firm management and the other is related to firm performance (PERF). In addition, Daniel et al. (2020) propose both short- and long-run behavioral factors. They suggest that the short-run factor (PEAD) is likely driven by investor inattention, whereas the long-run factor is likely driven by long-term overreaction. All of these new factor models are extremely powerful in explaining the cross-section of returns in the stock market.

In this paper, we aim to inspect the underlying economic mechanism for some of these newly proposed factors, especially those likely to be driven by underreaction, as well as for many anomalies that have been attributed to underreaction in previous literature. In particular, the list of our factors includes the RMW factor from the Fama-French five-factor model, the ROE factor from the Hou-Xue-Zhang four q-factors model, the gross profitability factor (PMU) from Novy-Marx (2013), the momentum factor (MOM) from Carhart (1997), the PERF factor from the Stambaugh-Yuan two mispricing factors model, and the short-run factor (PEAD) from Daniel-Hirshleifer-Sun's behavioral factor model.

We believe that it is important to understand the forces behind these prominent factors. First, like other prominent anomalies, the capital asset-pricing model (CAPM) alphas of these recent factors are abnormally large. For example, the ROE factor has a CAPM alpha of 0.76% per month. Second, these factor models can help account for an extremely large set of anomalies. As a result, one can use these factor models as benchmark models in many applications, including the performance attribution and evaluation of mutual/hedge funds, the computation of costs of capital in capital budgeting, the alpha calculation for a newly discovered anomaly, and so on. Consequently, given their well-grounded theoretical motivation and extraordinary empirical performance, exploring the economic mechanism underlying these base factors is worthwhile. For example, if risk is driving the profitability premium, and thus the ROE factor, we finally have a risk-based factor model which both is theoretically well grounded and can empirically account for a large set of cross-sectional anomalies. Therefore, it should be fruitful to further investigate the sources of risk. On the other hand, if mispricing is driving the profitability premium, it implies that many seemingly unrelated anomalies have a common mispricing component. Thus, searching for common behavioral biases underlying these anomalies is warranted.

More specifically, using media coverage as a proxy for investor attention, we investigate whether investor inattention plays a significant role in these factors or the corresponding underlying anomalies. In particular, we find that the underreaction-related anomalies underlying these factors are much more pronounced among firms with low media coverage in the previous month. In particular, among firms with low media coverage, the CAPM alpha spreads for the anomalies underlying the PEAD, MOM, ROE, PERF, PMU, and RMW factors are 1.29%, 1.76%, 1.53%, 2.18%, 1.24%, and 1.48%, respectively.[2] On the other hand, among firms with high media coverage, these CAPM alpha spreads are only 0.47%, 0.31%, 0.87%, 1.24%, 0.66%, and 1.05%, respectively.[3] This finding is consistent with the investor limited-attention interpretation. Beyond the standard double-sorting portfolio analysis, we also perform Fama-MacBeth regression analysis to control for several variables simultaneously. Consistent with the portfolio analysis, the interaction effect between media coverage and the underlying anomaly variables is mostly statistically significant with a consistent sign.

Apart from these factors, we also study the effect of media coverage on a broader set of anomalies that have been attributed to underreaction in previous literature. We choose these additional anomalies from the list of short-term anomalies identified by Daniel et al. (2020) and the underlying anomalies behind the composite factor PERF in Stambaugh and Yuan (2017), which are likely to be driven by investor underreaction, as they have argued.[4] This additional list of underreaction-related anomalies includes standardized unexpected earnings (SUE), revision in analysts' forecasts (RE), industry momentum (IndMom), return on assets (ROA), the number of consecutive quarters with an increase in earnings over the same quarter in the prior year (NEI), the Campbell et al. (2008) failure probability (FP), and Ohlson's (1980) score (OS). The main finding is similar to those based on the other factors. These anomalies tend to be much more pronounced among firms with low media coverage. Taking all the anomalies together, we find that the average CAPM alpha spread of these anomalies is about 1.38% per month among firms with low media coverage and 0.59% per month among firms with high media coverage. In addition, this media effect is remarkably consistent across these underreaction-related anomalies.

Moreover, most of the abnormal alpha spread among firms with low media coverage comes from the short leg of the anomalies (i.e., the relatively overpriced firms). The short leg has an average CAPM alpha of –1.17% per month, whereas the long leg has an average CAPM alpha of a mere 0.21% per month. This asymmetric effect is consistent with the notion that overpricing is more prevalent than underpricing, probably because of short-sale impediments. Thus, these anomalies are likely derived from the interaction effect between limited attention and limits to arbitrage. That is, limited attention leads to initial underreaction to firm-level information, such as SUE, and thus initial mispricing, and limits to arbitrage, especially short-sale impediments, prevent the complete correction of this initial mispricing at the portfolio-formation period. Thus, it is the interaction between limited attention and limits to arbitrage that leads to the final equilibrium overpricing (underpricing) of firms with adverse (favorable) information. That is, by sorting on an anomaly variable that contains useful information ignored by investors, we can observe the return predictability pattern.

Further, we also examine the stock-price movements around the subsequent earnings-announcement dates and find that, on average, firms classified in the long leg of the anomalies tend to have higher earnings surprises than firms classified in the short leg of the anomalies, and this effect is especially strong among firms with low media coverage. Here, the earnings surprises are measured by both SUE and the cumulative abnormal return around earnings announcements. This evidence suggests that both investors and analysts have made systematic expectation errors on firms' earning ability, probably because of limited attention to past news. That is, because of limited attention, the earning ability of firms with good news tends to be underestimated by both analysts and investors. Hence, firms classified in the long leg (short leg) are relatively underpriced (overpriced), especially for firms with low media coverage.

To alleviate the concern that our media coverage is correlated with firm size, we show that our results are robust after controlling for size. In particular, we form a size-orthogonalized media-coverage measure by regressing firm-level media coverage onto firm size. We show that the anomalies' spreads are also more pronounced among firms with low size-orthogonalized media coverage. Moreover, as a placebo test, we show that media coverage does not exert a significant effect on overreaction-related anomalies, highlighting the special role of media coverage in underreaction-related anomalies. Overall, the above evidence suggests that limited attention, coupled with limits to arbitrage, plays a significant role in these new prominent factors and in many underreaction-related anomalies as well. Thus, we further examine the possibility that these new factors are driven by mispricing. Again, take the profitability premium as an example. If mispricing is the main driver, the profitability premium should be more pronounced among firms with higher limits to arbitrage. With higher limits for professional investors to arbitrage, the mispricing is more difficult to be countervailed and more likely to be sustained. Following Pontiff (2006) and Stambaugh et al. (2015), we use firm-level idiosyncratic volatility as a proxy for limits to arbitrage and find that most of these factors and anomalies indeed earn substantially larger returns among firms with higher limits to arbitrage.

More specifically, using idiosyncratic return volatility as a proxy for limits to arbitrage, we find that the average Fama-French five-factor model (FF5)-adjusted alpha spread across all of the 13 anomalies is 1.10% per month among firms that are difficult to arbitrage, but only 0.27% per month among firms that are easy to arbitrage. We also use a composite arbitrage cost score as a measure of limits to arbitrage for our robustness check. In particular, the composite score is based on the firm's idiosyncratic return volatility, number of institutional investors, institutional holding shares, credit rating, dollar trading volume, bid-ask price spread, and Amihud illiquidity. We find that the average anomalies are also much more pronounced among firms with a higher composite arbitrage cost score. Moreover, the short legs of anomalies account for the majority of the anomalous returns. For example, among firms with high idiosyncratic volatility, the short leg has an average FF5-adjusted alpha of –1.23%, whereas the long leg has an average FF5-adjusted alpha of only –0.12% per month. This finding is again consistent with the notion that mispricing, especially overpricing, among firms with higher limits to arbitrage is harder for arbitrageurs to correct. More specifically, limited attention leads to initial overpricing (underpricing) in firms with adverse (favorable) information such as low (high) SUE. However, this initial mispricing is more difficult for arbitrageurs to correct among firms with high limits to arbitrage relative to firms with low limits to arbitrage. In addition, the overpricing is more difficult to correct because of short-sale impediments.

Lastly, we explore the possibility of systematic risk in these new factors and the underreaction-related anomalies. More specifically, we link the time-series variation in these anomaly return spreads to a set of well-known macro-related variables that have been shown to have predictive power for the aggregate market risk premium. If systematic risks are the main forces behind the anomalous return or factors, then these macro-related variables should also have power in predicting the anomalies and the factor premia. However, we find that these macro-related variables have very weak power in predicting anomalies and factor returns. In addition, many factor-return spreads are positive during bad times such as recessions, suggesting that exposure to these well-known macro-related risks is not much greater for firms in the long leg relative to firms in the short leg. Moreover, Savor and Wilson (2013) find that excess market returns on macro news announcement days are about 10 times larger than those on nonannouncement days, suggesting a disproportionately large fraction of risk premia on macro news announcement days. Indeed, Savor and Wilson (2014) show that the CAPM performs much better during macro news announcement days. Hence, if macro risk is responsible for the factor premia, we should expect the factor premia to be much larger on announcement days than on nonannouncement days. However, we find that all of the factor premia and underreaction-related anomalies are similar on both announcement and nonannouncement days. If anything, the return spreads are lower during macro news announcements. The above evidence again supports the view that traditional macro risk is unlikely to be the main source of the observed factor premia or the underlying anomalies.

In terms of related studies, our paper belongs to a vast literature that investigates the role of limited attention in asset-pricing anomalies. In particular, our evidence suggests that inattention-induced underreaction plays an important role in many prominent factors. Prior studies also find that inattention plays an important role in other anomalies, such as postearnings announcement drifts (DellaVigna and Pollet 2009 and Hirshleifer et al. 2011), innovative efficiency (Hirshleifer et al. 2013), price momentum (Hou et al. 2009 and Da et al. 2014), economic links (Cohen and Frazzini 2008), and gradual information diffusion across the borders (Huang 2015), among others. Early studies, including Cohen and Frazzini (2008), Cohen and Lou (2012), Hou (2007), and Huang (2018), find evidence on information diffusion across firms, and DellaVigna and Pollet (2007) find information diffusion across time horizons. More recently, Gonzalez et al. (2019) find evidence on slow information diffusion across geographic segments.

Early studies tend to focus on the unconditional effect of inattention or the time-series variation in inattention. For example, DellaVigna and Pollet (2009) find that Friday announcements have a 15% lower immediate response and a 70% higher delayed response. In addition, they find that a portfolio investing in Friday drift earns substantial abnormal returns. More recently, Duan et al. (2020) find that the performance of underreaction-related anomalies varies with market-wide time-series investor attention. Instead of examining the time-series variation, our study investigates the rich cross-sectional heterogeneity of the underreaction-related anomalies across firms with different levels of media coverage. Moreover, our study covers a broad set of underreaction-related anomalies. Relatedly, Fang and Peress (2009) also study the effect of media coverage on asset prices, and they find that firms with more media coverage tend to earn lower subsequent returns. Whereas Fang and Peress (2009) focus on the unconditional effect of media coverage on asset returns, we examine the interaction effect of media coverage and a broad set of underreaction-related anomalies.

Recently, Fama-French's five-factor model; Hou-Xue-Zhang's q-4 factor model; Stambaugh and Yuan's mispricing factor model; and Daniel, Hirshleifer, and Sun's behavioral factor model have attracted a lot of attention in the literature. The RMW, ROE, PERF, and PEAD factors are among the new factors in those models. Thus, our evidence shows that these new factors are at least partially a result of limited attention coupled with limits of arbitrage, and their ability to account for many other anomalies may also be due to the fact that these anomalies are partially driven by limited attention as well, rather than completely a result of their exposure to systematic risk. Here, we focus on the factors that are more likely to be driven by underreaction, because there is likely an interaction effect with media coverage for these factors. On the other hand, it is not clear how media coverage, or more generally, investor attention, should affect other types of anomalies such as overreaction-related anomalies, as we discuss in more detail in Section 4.[5] Thus, we do not examine how inattention affects factors whose underlying anomalies are less likely to be driven by underreaction, and we use overreaction-related anomalies only as a placebo test.

Lastly, our study is also related to the large literature on limits to arbitrage and anomalies. Notable earlier papers include Wurgler and Zhuravskaya (2002) on index addition announcements; Ali et al. (2003) on the value premium; Nagel (2005) on turnover, the value premium, analyst forecast dispersion, and volatility; Zhang (2006) on momentum-related anomalies; Mashruwala et al. (2006) on accruals; Li and Zhang (2010) on net operating assets, net stock issues, and investment growth; Duan et al. (2010) on short interest; Lam and Wei (2011) on asset growth; and Chu et al. (2020) on 11 well-known asset-pricing anomalies, among others. These studies typically find that anomalies tend to be more pronounced among firms with higher limits to arbitrage.

We organize the rest of the paper as follows. We describe data sources and variable definitions in Section 2. Section 3 presents our main results using portfolio analysis and Fama-MacBeth regressions. Section 4 further explores several potential underlying sources of mispricing. Section 5 concludes.

2. Data Description and Summary Statistics

This section describes how we construct our key anomaly variables and media coverage. Summary statistics on various underreaction-related portfolios and the underlying characteristics are also reported. Our sample includes all NYSE, AMEX, and NASDAQ (Center for Research in Security Prices (CRSP) exchange codes 1, 2, and 3) listed ordinary common stocks (CRSP share codes 10 and 11). We delete financial stocks, stocks with negative book equity, and stocks with a price of less than $1.

2.1. Data Sources and Variable Definition

The data sources and variable construction are described in this section. Our data come from six sources. Stock return data are from CRSP. Firm accounting-information data are obtained from Compustat. Analyst forecasts data are from the Institutional Brokers' Estimate System (I/B/E/S). Data on institutional holdings are obtained from Thomson Reuters. Data on macro-related variables are from Amit Goyal's web page and Sydney Ludvigson's web page. Lastly, data on macro news releases are obtained from the Federal Reserve System and the Bureau of Labor Statistics (BLS).

Our media-coverage data are from RavenPack, available from 2000 to 2018. Following Gao et al. (2018), we use the Dow Jones edition of RavenPack news data and include only news stories with an Event Novelty Score of 100 to avoid double-counting the same event of a company. We further require news to have a relevance score of 100 to filter out nonessential news. Following Fang and Peress (2009) and Tetlock (2010), we measure media coverage as the log of one plus the number of news articles published on the Dow Jones newswire in the past month. With this continuous measure of media coverage, we can also perform bivariate portfolio sorts (such as five by five) based on media coverage and individual stock characteristics. We also construct a size-orthogonalized media-coverage measure by regressing the original firm-level media coverage on the log of firm's market capitalization cross-sectionally. To alleviate the effect caused by extreme values or outliers, we winsorize these two variables at the 5% and 95% level before the regression. In addition, as a robustness check, we also use media coverage as a dummy variable. A media dummy denotes whether the company has been reported on by Dow Jones news in the past month. The media dummy is assigned a value of zero if no report has been made in the past month, and one otherwise.

The media, including newswires and publications, constitute an important component of a country's information environment for disseminating information to the public (Bushman et al. 2004, Tetlock 2010, Peress 2014). It is well known that investors rely on newswires and publications as primary information sources for investing (e.g., Roll 1988 and Griffin et al. 2011), and coverage in popular newspapers catches investors' attention (e.g., Engelberg and Parsons 2011 and Solomon et al. 2014). In addition, the news data from RavenPack allow us to examine the asset-pricing effect of attention to different types of information, such as insider-trading behavior, technical indicators, and fundamental values. The news data also allow us to explore the heterogeneity among firms who get covered once, then disappear from being covered, compared with firms that get covered repeatedly month by month. Thus, following Fang and Peress (2009), we choose to focus on media attention as our main attention proxy and study how media coverage affects anomalies' behavior.

However, previous studies have proposed various alternative proxies for investor attention. Thus, as a robustness check, we also construct a composite attention index based on individual proxies including: (1) abnormal Google search volume, which is calculated as the log difference between the Google search volume in past one month and the average of the Google search volume over past 12 months, following Da et al. (2011); (2) media coverage, which is introduced before; (3) abnormal EDGAR downloads, which are calculated as the log difference between the number of EDGAR downloads in the past month and the average number over the past 12 months, by employing the Ryans (2017) method to extract the human downloads;[6] (4) abnormal trading volume, which is calculated as the log difference of trading volume in the past month and the average trading volume over the past 12 months; (5) past return, which is the cumulative return in the past 12 months following Aboody et al. (2010); (6) analyst coverage, which is the number of estimates for the earnings forecasts for the current fiscal year; (7) mutual fund net flow, which is the percentage change of the institutional holdings from quarter $t-2$ to quarter $t-1$, following Dasgupta et al. (2011); (8) absolute value of earnings surprise, which is the absolute value of the ratio of the difference between actual earnings per share (EPS) and the consensus forecast EPS over the stock price; and (9) 52-week high, which is the ratio of the current price over the highest price in the past 52 weeks, following George and Hwang (2004). We construct the composite attention index as the average z-score of these nine attention proxies.[7]

We examine six factors that are more likely to be driven by underreaction. More specifically, these factors include the operating profitability factor (RMW) from Fama and French's (2015) five-factor model, the profitability factor (ROE) from the Hou et al. (2015) q-factor model, the profitable-minus-unprofitable factor (PMU) from Novy-Marx (2013), the momentum factor (MOM) from Carhart's (1997) four-factor model, the performance-related mispricing factor (PERF) from Stambaugh and Yuan's (2017) mispricing factor model, and the short-run behavior factor (PEAD) from the Daniel et al. (2020) behavioral factor model.

Following these original studies, the corresponding firm characteristics underlying these factors are: (1) operating profitability (*OP*) for RMW, calculated as the ratio of a firm's operating profits (revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses) to its equity following Fama and French (2015); (2) return on equity (*ROE*) for ROE following Hou et al. (2015); (3) gross profitability (*GP*) for PMU, calculated as the ratio of a firm's gross profits (revenues minus cost of goods sold) to its assets following Novy-Marx (2013); (4) stock returns over the previous 11 months with a one-month gap (*MOM*) for MOM following Jegadeesh and Titman (1993) and Daniel et al. (2020); (5) a composite score based on financial distress, O-score, momentum, gross profitability, and return-on-assets (*PERF*) for PERF, following Stambaugh and Yuan (2017); and (6) the cumulative abnormal returns around earnings announcements (*CAR*) for PEAD, following Chan et al. (1996) and Daniel et al. (2020).

In addition, Daniel et al. (2020) classify their anomalies into a few categories, and they argue that the short-term anomaly list in their paper is likely to be driven by investor underreaction. Thus, we consider seven additional underreaction-related anomalies, including: (1) the earnings surprise of the latest quarterly earnings announcement date (*SUE*), calculated as the change in quarterly earnings per share from its value four quarters ago divided by the standard deviation of this change over the prior eight quarters, following Daniel et al. (2020); (2) the revision in analysts' forecast (*RE*), calculated as the average change in the consensus analysts' forecast over the past six months following Chan et al. (1996); (3) the industry momentum (*IndMom*), calculated as the equal-weighted average return of the industry in previous month; (4) the return on asset (*ROA*) following Daniel et al. (2020); (5) the number of consecutive quarters (up to eight quarters) with an increase in earnings over the same quarter in the prior year (*NEI*), following Daniel et al. (2020); (6) the failure probability (*FP*) following Campbell et al. (2008) and Hou et al. (2020); and (7) the O-score (*OS*) on bankruptcy probability following Ohlson (1980) and Hou et al. (2020). We choose these firm-level variables because they either are the underlying anomaly variables behind the composite factor, *PERF*, or are in the short-term anomaly list in Daniel et al. (2020), which are likely to be driven by investor underreaction, as they have argued. Indeed, existing studies, such as Bernard and Thomas (1989), George and Hwang (2004), and Bouchaud et al. (2019), tend to attribute anomalies based on medium-term past returns, past performance, and analyst revision to underreaction. Again, we acknowledge that we have probably missed some potential underreaction-related anomalies, such as those related to economic links.

Thirteen control variables are associated with conducting Fama-MacBeth tests: (1) the beta (*Beta*), estimated from the CAPM model by using past 60 months data; (2) the size (*LME*), calculated as the logarithm of market capitalization; (3) the book-to-market ratio (*LBM*), calculated as the logarithm of the book-to-market ratio, following Fama and French (1992); (4) the short-term return (Ret_{-1}), calculated as the return in the past one month; (5) the momentum (*MOM*), introduced before; (6) the long-term return ($Ret_{-36,-13}$), calculated as the cumulative return from the prior 36 months to the prior 12 months, following De Bondt and Thaler (1985); (7) Amihud illiquidity (*ILLIQ*), calculated as the logarithm of the average daily ratio of the absolute stock return to the dollar trading volume within past 12 months, following Amihud (2002); (8) the idiosyncratic volatility (*IVOL*), calculated as the residual sum of squares of the Fama and French's (1993) three-factor model in each month, following Ang et al. (2006): (9) the institutional ownership (*Ownership*), measured as the percentage of outstanding shares held by institutional investors; (10) the abnormal trading volume (*ABVOL*), calculated as the log difference between the dollar trading volume in the previous month and its average value over the past 12 months; (11) analyst coverage (*Analyst*), measured as the number of estimates for the earnings forecasts for the current fiscal year; (12) composite arbitrage cost score (*Arbitrage*), defined in Section 2.3; and (13) Fama-French 48 industry dummies.

The sample period is from 1976 to 2018 for anomalies using Compustat quarterly data (*SUE*, *CAR*, *ROE*, *ROA*, *NEI*, and *FP*), 1978 to 2018 for anomalies using I/B/E/S annual forecast data (*RE*), 2000 to 2018 for media coverage, and 1965 to 2018 for other anomalies (*MOM*, *IndMom*, *OS*, *GP*, *OP*, and *PERF*).

2.2. Overreaction-Related Anomalies

As a placebo test, we also study the interaction effect between media coverage and overreaction-related anomalies. For example, Lakonishok et al. (1994) argue that investor extrapolation could lead to overreaction, which could only be weakly related to investor attention. Thus, media coverage might play a less important role among these anomalies. As a result, we consider a set of anomalies that previous studies tend to attribute to overreaction. For example, the evidence in Lakonishok et al. (1994) and Gennaioli et al. (2016) suggests that the value-growth anomaly and the investment-based anomalies are likely to be driven by extrapolation-induced overreaction. Thus, following Daniel et al. (2020), we construct value-growth anomalies and investment-based anomalies, including: (1) book-to-market equity (*B*/*M*), following Rosenberg et al. (1985) and Fama and French (1992); (2) earnings-to-price (*E*/*P*), following Basu (1983); (3) cash flow-to-price (*CF*/*P*), following Lakonishok et al. (1994); (4) net payout yield (*NPY*), following Boudoukh et al. (2007); (5) equity duration (*DUR*), following Dechow et al. (2004) and Hou et al. (2020); (6) asset growth (*AG*), following Cooper et al. (2008); (7) net operating assets (*NOA*), following Hirshleifer et al. (2004); (8) investment-to-asset ratio (*IVA*), following Lyandres et al. (2008); (9) investment growth (*IG*), following Xing (2008); (10) inventory growth (*IvG*), following Belo and Lin (2012); (11) inventory changes (*IvC*), following Thomas and Zhang (2002); (12) operating accruals (*ACC*), following Sloan (1996) and Stambaugh and Yuan (2017); (13) percent operating accruals (*POA*), following Hafzalla et al. (2011); (14) percent total accruals (*PTA*), following Hafzalla et al. (2011); (15) net share issuance (*NSI*), following Pontiff and Woodgate (2008); (16) composite share issuance (*CSI*), following Daniel and Titman (2006); and (17) the average portfolio of these 16 anomalies (*Average*).

2.3. Proxies for Arbitrage Costs

We also study the interaction effect between limits to arbitrage and underreaction-related anomalies to check whether the excess return could be explained by mispricing. Three variables are employed as proxies for arbitrage cost. The first proxy is idiosyncratic volatility (IVOL), which is the residual sum of squares of the Fama-French three-factor model in each month, following Ang et al. (2006). The second proxy is institutional ownership, which is the percentage of outstanding shares held by institutional investors at the portfolio-formation date. The third proxy is a composite score, which is constructed based on seven commonly used proxies for limits to arbitrage in prior studies (e.g., Amihud 2002, Ali et al. 2003, Nagel 2005, Mashruwala et al. 2006, Duan et al. 2010, Lam and Wei 2011, and Avramov et al. 2013). These variables include idiosyncratic volatility, number of institutional

Table 1. Summary Statistics of the Anomalies: Correlations Between Anomaly Variables and Media Coverage

	SUE	*CAR*	*RE*	*MOM*	*IndMom*	*ROE*	*ROA*	*NEI*	*1/FP*	*1/OS*	*GP*	*OP*	*1/PERF*	*Average*
Media	0.06	0.05	0.08	0.11	0.01	0.16	0.17	0.08	0.21	0.22	0.06	0.21	0.22	0.13

Notes. This table and Tables 2 and 3 report the summary statistics of the anomalies. This table presents the time-series average of cross-sectional Spearman-rank correlations between anomaly value and media coverage. The sample period is from 2000 to 2018.

investors, institutional ownership, credit rating, dollar trading volume, bid-ask price spread, and Amihud's (2002) illiquidity.

2.4. Macroeconomic Variables

To test whether these factors or anomalies comove with macroeconomic conditions, we use several macro-related variables that have been shown to be related to the aggregate risk premium. Specifically, the list of variables includes the 14 equity premium predictors, as in Welch and Goyal (2008); the surplus ratio, as in Campbell and Cochrane (1999), and the macro and financial uncertainty indexes, as in Jurado et al. (2015). The 14 predictors in Welch and Goyal (2008) include log dividend-price ratio (*DP*), log dividend yield (*DY*), log earnings-price ratio (*EP*), log dividend-payout ratio (*DE*), stock excess return volatility (*SVAR*), cross-sectional premium (*CSP*), book-to-market ratio (*BM*), net equity issuance (*NTIS*), Treasury bill rate (*TBL*), long-term yield (*LTY*), long-term return (*LTR*), term spread (*TMS*), default yield spread (*DFY*), default return spread (*DFR*), and inflation (*INFL*). These data are available at Amit Goyal's web page[8] for the period from 1965 to 2018, except for *CSP*, which is in the period from 1965 to 2002. In addition, we add the consumption surplus ratio (*SPLUS*), as in Campbell and Cochrane (1999), which is computed as the exponentially weighted moving average of the past consumption growth by following Wachter (2006). To convert our quarterly surplus ratio to monthly frequency, we assign the most recent quarterly surplus ratio as our monthly measure. Last, we collect macro and financial uncertainty indexes (*JLN_Mac* and *JLN_Fin*) from Sydney Ludvigson's website[9] for the period from 1965 to 2018.

2.5. Macro News Announcements

To examine whether these factors or anomalies earn higher return during macroeconomic news announcement dates, we obtain dates of prescheduled monthly macroeconomic news announcements about the Federal Open Market Committee (FOMC) interest rate from the Federal Reserve from 1978 to 2018 and unemployment rates and inflation from the BLS from 1958 to 2018. In addition, we use the consumer price index (CPI) before February 1971 and replace it with the producer price index (PPI) because PPI numbers are always released a few days earlier than CPI numbers. Following Kuttner (2001), we assume that, before February 1994, the FOMC decision became publicly available one day after its meeting. Lastly, we adjust the date to the next trading day if announcements are made on nontrading days and exclude all the unscheduled announcements.

2.6. Unconditional Sorts for Underreaction-Related Anomalies

Table 1 reports the time-series average of the cross-sectional correlation between the underlying anomaly variables and media coverage and shows that the correlations tend to be very low, most close to zero.[10] Table 2 reports the correlation between control variables and media coverage, and, as we expected, media coverage is highly correlated with size, liquidity, analyst coverage, and arbitrage cost. In the following analysis, we employ the Fama-MacBeth tests to control these variables. Table 3 reports the monthly value-weighted portfolio returns, CAPM alphas, Fama-French three-factor alphas, and Fama-French five-factor alphas from 2000 to 2018.[11] The average portfolio has a raw return spread, CAPM alpha spread, Fama-French three-factor alpha spread, and Fama-French five-factor alpha spread of 0.47%, 0.70%, 0.74%, and 0.34% per month, respectively. All are statistically significant, except for the raw return spread, which is also marginally significant with *t*-statistic (*t*-stat) of 1.72. In addition, the firms in the short leg account for a majority of abnormal returns. Specifically, the top-quintile portfolio has a CAPM alpha of 0.12%, whereas the bottom-quintile portfolio has a CAPM alpha of −0.58%. Thus, about 83% of the average anomaly CAPM alpha comes from the short leg. Moreover, to address potential market micro structure issues, we skip one month immediately after portfolio formation, and we find that the return spread remains very similar. Lastly, as expected, the Fama-French five-factor alphas

Table 2. Summary Statistics of the Anomalies: Correlations Between Control Variables and Media Coverage

	Beta	*LME*	*LBM*	Ret_{-1}	*MOM*	$Ret_{-36,-13}$	*ILLIQ*	*IVOL*	*Ownership*	*ABVOL*	*Analyst*	*Arbitrage*	*Average*
Media	0.03	0.51	−0.18	0.05	0.11	0.18	−0.51	−0.16	0.35	0.23	0.41	−0.47	0.05

Notes. This table and Tables 1 and 3 report the summary statistics of the anomalies. This table presents the time-series average of cross-sectional Spearman-rank correlations between control variable and media coverage. The sample period is from 2000 to 2018.

Table 3. Summary Statistics of the Anomalies: Anomaly Returns

	Excess teturn			CAPM alpha			FF3 alpha			FF5 alpha		
Anomaly	P1	P5	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1
SUE	0.24	0.42	0.18	−0.18	0.06	0.24	−0.14	0.14	0.28	−0.05	0.04	0.09
	(0.66)	(1.32)	(1.29)	(−1.56)	(0.72)	(1.84)	(−1.47)	(1.97)	(2.17)	(−0.46)	(0.54)	(0.61)
CAR	0.15	0.59	0.44	−0.36	0.14	0.50	−0.32	0.19	0.51	−0.19	0.33	0.52
	(0.34)	(1.47)	(2.45)	(−2.25)	(1.21)	(2.81)	(−2.14)	(2.21)	(2.66)	(−1.20)	(3.68)	(2.54)
RE	0.23	0.68	0.45	−0.33	0.27	0.60	−0.45	0.25	0.70	−0.30	0.18	0.48
	(0.46)	(1.66)	(1.58)	(−1.47)	(1.85)	(2.15)	(−2.26)	(1.66)	(2.74)	(−1.37)	(1.11)	(1.51)
MOM	0.09	0.52	0.43	−0.56	0.11	0.67	−0.54	0.12	0.66	−0.18	0.10	0.28
	(0.13)	(1.30)	(0.93)	(−1.85)	(0.54)	(1.68)	(−1.92)	(0.74)	(1.69)	(−0.60)	(0.53)	(0.64)
IndMom	0.39	0.41	0.02	−0.03	0.10	0.12	0.02	0.11	0.09	0.02	0.03	0.01
	(1.11)	(1.35)	(0.09)	(−0.17)	(0.78)	(0.52)	(0.11)	(0.97)	(0.39)	(0.10)	(0.22)	(0.04)
ROE	−0.04	0.45	0.49	−0.64	0.12	0.76	−0.58	0.18	0.76	−0.17	0.04	0.21
	(−0.06)	(1.56)	(1.34)	(−2.29)	(1.83)	(2.60)	(−3.13)	(3.14)	(3.45)	(−1.00)	(0.74)	(1.07)
ROA	−0.26	0.47	0.73	−0.93	0.12	1.05	−0.90	0.21	1.11	−0.33	0.11	0.44
	(−0.37)	(1.57)	(1.61)	(−2.77)	(1.51)	(3.19)	(−3.87)	(3.14)	(4.20)	(−1.65)	(1.57)	(1.93)
NEI	0.30	0.46	0.15	−0.10	0.11	0.21	−0.08	0.17	0.24	−0.03	0.01	0.04
	(0.84)	(1.47)	(0.89)	(−1.17)	(0.89)	(1.29)	(−1.02)	(1.43)	(1.49)	(−0.35)	(0.10)	(0.25)
1/FP	−0.34	0.41	0.75	−1.18	0.11	1.29	−1.22	0.13	1.35	−0.62	0.00	0.63
	(−0.41)	(1.47)	(1.19)	(−2.86)	(1.35)	(2.94)	(−3.53)	(1.71)	(3.58)	(−1.94)	(0.04)	(1.67)
1/OS	0.10	0.33	0.23	−0.53	−0.05	0.48	−0.53	0.05	0.58	−0.11	0.05	0.16
	(0.16)	(1.03)	(0.62)	(−2.00)	(−0.55)	(1.93)	(−2.38)	(0.84)	(2.45)	(−0.61)	(0.84)	(0.80)
GP	0.09	0.53	0.45	−0.32	0.22	0.54	−0.33	0.24	0.57	−0.28	0.06	0.33
	(0.21)	(1.96)	(2.16)	(−2.66)	(2.22)	(3.19)	(−2.63)	(2.46)	(3.22)	(−2.21)	(0.52)	(1.83)
OP	−0.20	0.48	0.68	−0.85	0.15	0.99	−0.80	0.20	1.00	−0.23	0.03	0.27
	(−0.30)	(1.74)	(1.49)	(−2.38)	(2.39)	(2.72)	(−3.69)	(3.42)	(4.19)	(−1.31)	(0.78)	(1.60)
1/PERF	−0.73	0.45	1.18	−1.48	0.12	1.60	−1.51	0.19	1.70	−0.87	0.08	0.95
	(−0.90)	(1.54)	(2.04)	(−3.74)	(1.38)	(4.05)	(−4.85)	(2.75)	(4.96)	(−3.27)	(1.03)	(3.15)
Average	0.00	0.48	0.47	−0.58	0.12	0.70	−0.57	0.17	0.74	−0.26	0.08	0.34
	(0.00)	(1.54)	(1.72)	(−3.04)	(1.95)	(3.68)	(−4.02)	(3.62)	(4.45)	(−2.01)	(1.51)	(2.08)

Notes. This table and Tables 1 and 2 report the summary statistics of the anomalies. This table presents anomalies' monthly mean excess returns, CAPM alphas, FF3 alphas, and FF5 alphas. The sample period is from 2000 to 2018. Monthly returns and alphas are reported in percentages. Newey and West (1987) six-lag adjusted *t*-statistics are reported in parentheses.

are lower for some of the anomalies because the factor RMW is correlated with several of our anomaly variables. We also check the Spearman-rank correlation coefficients between these long-short anomaly portfolios in Table B1 in the online appendix. Some of the portfolios, such as *ROE* and *ROA*, have a high correlation, as expected, because the underlying characteristics are similar. On the other hand, some anomaly portfolios have a low correlation with other portfolios. For example, the *OP* and *CAR* have a weak correlation with each other. For each long-short portfolio, the average correlations with other portfolios are not particularly high, ranging from 14% to 54%. The time-series average of the cross-sectional correlations of these anomaly's characteristics also have a similar pattern, as reported in Table B1 in the online appendix.

3. Empirical Analysis: Media Coverage and Anomaly Returns

In this section, we first perform our main double-sorting portfolio analysis. Then, we use the Fama and MacBeth (1973) regression to control for variables. Lastly, we investigate the subsequent earnings-announcement behavior after portfolio-formation periods.

3.1. Double-Sorted Portfolios

In this section, we present the key results of our paper. We perform a series of double-sorting exercises, first by investor attention, then by firm-level characteristics underlying factors or anomalies. The proxy we adopt for investor inattention is media coverage. The basic idea is that the market doesn't always immediately incorporate new information into prices, and sometimes underreaction could happen because investors fail to trade on the new information and let it fully reflect in prices in a timely manner. For example, investors might not pay enough attention or may not be aware of the new information. In addition, even if investors are aware of and fully attentive to the news, investors may still underreact to the news because of behavioral bias, such as anchoring bias or conservatism.

The focus of our study is how investors' inattention, rather than other behavioral biases, are affecting the underreaction-related anomalies. Following this logic,

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if investor inattention at least partly drives the underreaction, then underreaction should be more pronounced among firms with low media coverage in the previous month. Thus, as prices gradually incorporate past news, the underreaction-induced anomalies should earn higher returns among firms with low media coverage than among firms with high media coverage in the portfolio-formation periods. Indeed, inattention has been shown to be responsible for many asset-pricing anomalies. See DellaVigna and Pollet (2009) and Hirshleifer et al. (2011) for postearnings announcements drift; Bali et al. (2014) for underreaction to liquidity shocks; Hirshleifer et al. (2013) for innovation efficiency, Huang (2015) for gradual cross-board information flow; and Da et al. (2014) for momentum, among others. Here, we consider the effect of inattention on a much broader set of underreaction-related anomalies and prominent factors.

Tables 4 and 5 present the main result. As we can see, consistent with our prediction, most of the anomalies underlying these factors are significantly stronger among firms with low media coverage in the portfolio-formation periods. Among firms with low media coverage, the average anomaly raw return spread (the last row) is about 1.16% per month (t-stat = 3.50). On the other hand, among firms with high media coverage, the average return spread is only 0.39% per month (t-stat = 1.62). The magnitude of the difference between stocks with low and high media coverage is both economically large and statistically significant at 0.77% per month (t-stat = 3.55). The CAPM alphas in Table 4 yield a pattern similar to raw excess returns.[12]

To control for more potential risk factors, Table 5 reports the Fama-French three-factor model (FF-3) factor-adjusted alphas. The main pattern based on raw returns still holds. More specifically, among firms with low media coverage, the average alpha across these anomalies is about 1.39% per month (t-stat = 5.99). On the other hand, among firms with high media coverage, the average alpha is only 0.60% per month (t-stat = 3.55).

Table 4. Anomaly Returns with Low and High Media Coverage: Excess Returns and CAPM Alphas

	Excess return							CAPM alpha						
	Low media			High media			H-L	Low media			High media			H-L
Anomaly	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1
SUE	−0.07	0.80	0.86	0.23	0.41	0.18	−0.68	−0.58	0.35	0.93	−0.21	0.05	0.25	−0.68
	(−0.15)	(1.86)	(2.64)	(0.62)	(1.27)	(1.12)	(−1.89)	(−2.16)	(1.79)	(2.72)	(−1.44)	(0.39)	(1.53)	(−1.81)
CAR	−0.42	0.83	1.25	0.24	0.65	0.41	−0.84	−0.96	0.33	1.29	−0.27	0.20	0.47	−0.82
	(−0.88)	(1.79)	(3.91)	(0.62)	(1.62)	(1.69)	(−2.20)	(−3.2)	(1.43)	(4.03)	(−1.75)	(1.29)	(1.92)	(−2.17)
RE	−0.62	0.57	1.19	0.33	0.44	0.11	−1.08	−1.24	0.05	1.29	−0.21	0.03	0.25	−1.04
	(−0.91)	(1.15)	(2.37)	(0.72)	(1.01)	(0.37)	(−2.60)	(−2.94)	(0.18)	(2.69)	(−1.00)	(0.16)	(0.82)	(−2.49)
MOM	−0.98	0.44	1.42	0.37	0.51	0.14	−1.27	−1.76	0.00	1.76	−0.22	0.09	0.31	−1.45
	(−1.25)	(0.96)	(2.38)	(0.68)	(1.17)	(0.30)	(−2.34)	(−3.98)	(−0.01)	(3.34)	(−0.73)	(0.37)	(0.70)	(−2.79)
IndMom	0.31	0.64	0.33	0.44	0.36	−0.07	−0.40	−0.18	0.27	0.45	0.03	0.04	0.01	−0.44
	(0.76)	(1.57)	(0.87)	(1.38)	(1.14)	(−0.30)	(−1.25)	(−0.76)	(1.01)	(1.16)	(0.19)	(0.26)	(0.03)	(−1.40)
ROE	−0.56	0.68	1.24	−0.11	0.47	0.58	−0.66	−1.27	0.26	1.53	−0.74	0.13	0.87	−0.66
	(−0.77)	(1.72)	(2.42)	(−0.19)	(1.59)	(1.57)	(−1.70)	(−3.06)	(1.27)	(3.31)	(−2.59)	(1.35)	(2.98)	(−1.68)
ROA	−0.74	0.52	1.26	−0.20	0.44	0.63	−0.63	−1.48	0.11	1.60	−0.86	0.08	0.94	−0.66
	(−0.93)	(1.38)	(2.18)	(−0.31)	(1.43)	(1.59)	(−1.52)	(−3.27)	(0.46)	(3.33)	(−2.86)	(0.74)	(3.07)	(−1.58)
NEI	0.19	0.97	0.79	0.27	0.37	0.10	−0.69	−0.30	0.54	0.83	−0.13	0.02	0.15	−0.68
	(0.46)	(1.89)	(2.65)	(0.78)	(1.16)	(0.49)	(−2.23)	(−1.74)	(1.69)	(2.56)	(−1.27)	(0.12)	(0.78)	(−2.07)
1/FP	−1.27	0.47	1.74	−0.22	0.43	0.65	−1.09	−2.13	0.14	2.26	−1.05	0.12	1.17	−1.09
	(−1.42)	(1.53)	(2.41)	(−0.28)	(1.52)	(1.08)	(−2.42)	(−4.18)	(0.85)	(4.06)	(−2.57)	(1.25)	(2.64)	(−2.44)
1/OS	−0.49	0.44	0.92	0.17	0.34	0.17	−0.76	−1.16	−0.04	1.12	−0.37	−0.06	0.31	−0.81
	(−0.59)	(1.12)	(1.65)	(0.34)	(0.99)	(0.68)	(−1.55)	(−2.61)	(−0.25)	(2.38)	(−1.86)	(−0.48)	(1.51)	(−1.72)
GP	−0.26	0.83	1.09	0.01	0.55	0.54	−0.55	−0.76	0.47	1.24	−0.42	0.23	0.66	−0.58
	(−0.51)	(2.41)	(2.92)	(0.01)	(1.99)	(2.18)	(−1.44)	(−2.67)	(2.21)	(3.54)	(−3.06)	(1.78)	(3.30)	(−1.52)
OP	−0.71	0.50	1.21	−0.20	0.54	0.74	−0.47	−1.43	0.05	1.48	−0.84	0.20	1.05	−0.43
	(−0.91)	(1.27)	(2.15)	(−0.30)	(1.88)	(1.69)	(−1.28)	(−2.84)	(0.24)	(2.79)	(−2.38)	(2.13)	(2.84)	(−1.15)
1/PERF	−1.13	0.64	1.77	−0.44	0.43	0.88	−0.89	−1.93	0.25	2.18	−1.15	0.09	1.24	−0.93
	(−1.30)	(1.78)	(2.70)	(−0.63)	(1.38)	(1.82)	(−1.90)	(−3.98)	(1.37)	(4.26)	(−3.17)	(0.73)	(3.36)	(−2.02)
Average	−0.52	0.64	1.16	0.07	0.46	0.39	−0.77	−1.17	0.21	1.38	−0.50	0.09	0.59	−0.79
	(−0.86)	(1.70)	(3.50)	(0.14)	(1.45)	(1.62)	(−3.55)	(−4.51)	(1.40)	(5.12)	(−2.87)	(1.08)	(3.30)	(−3.65)

Notes. This table and Table 5 report the value-weighted average returns of portfolios double-sorted on media coverage and anomaly. We report the excess returns and CAPM alphas in this table and the alphas of the Fama-French three-factor model and the Fama-French five-factor model in Table 5. Media coverage is the natural log of one plus the number of news articles published on the Dow Jones newswire in the past month. All portfolios are rebalanced monthly. Average refers to the average return of these 13 anomalies. The sample period is from 2000 to 2018. Monthly returns and alphas are reported in percentages. Newey-West six-lag adjusted t-statistics are reported in parentheses.

Table 5. Anomaly Returns with Low and High Media Coverage: Alphas of Fama-French Three-Factor Model and Fama-French Five-Factor Model

	FF3 alpha							FF5 alpha						
	Low media			High media			H-L	Low media			High media			H-L
Anomaly	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1	P5-P1
SUE	−0.60	0.34	0.94	−0.14	0.13	0.27	−0.67	−0.49	0.27	0.75	0.00	0.01	0.01	−0.74
	(−2.48)	(1.73)	(2.89)	(−1.25)	(1.25)	(1.59)	(−1.76)	(−1.79)	(1.15)	(2.04)	(0.03)	(0.11)	(0.04)	(−1.78)
CAR	−0.98	0.28	1.26	−0.19	0.32	0.52	−0.74	−0.81	0.51	1.31	−0.09	0.46	0.55	−0.76
	(−3.87)	(1.40)	(3.73)	(−1.24)	(2.00)	(1.97)	(−1.86)	(−2.81)	(2.51)	(3.83)	(−0.57)	(2.58)	(1.94)	(−2.02)
RE	−1.39	−0.04	1.34	−0.26	0.07	0.33	−1.01	−1.10	0.03	1.12	−0.08	0.02	0.09	−1.03
	(−3.52)	(−0.18)	(2.78)	(−1.22)	(0.37)	(1.16)	(−2.48)	(−2.75)	(0.10)	(2.23)	(−0.34)	(0.08)	(0.26)	(−2.38)
MOM	−1.84	−0.04	1.79	−0.15	0.16	0.31	−1.48	−1.37	0.00	1.37	0.17	0.11	−0.06	−1.43
	−-4.36)	(−0.17)	(3.44)	(−0.52)	(0.73)	(0.70)	(−2.85)	(−3.17)	(0.00)	(2.47)	(0.49)	(0.42)	(−0.10)	(−2.67)
IndMom	−0.24	0.18	0.42	0.09	0.08	−0.02	−0.44	−0.12	0.18	0.30	0.08	−0.05	−0.13	−0.42
	(−1.14)	(0.73)	(1.18)	(0.49)	(0.55)	(−0.07)	(−1.40)	(−0.50)	(0.58)	(0.66)	(0.33)	(−0.31)	(−0.35)	(−1.27)
ROE	−1.29	0.22	1.51	−0.62	0.20	0.82	−0.69	−0.72	0.15	0.88	−0.23	0.01	0.25	−0.63
	(−3.84)	(1.16)	(3.86)	(−3.36)	(2.49)	(3.74)	(−1.78)	(−2.22)	(0.77)	(2.31)	(−1.41)	(0.13)	(1.23)	(−1.57)
ROA	−1.48	0.10	1.58	−0.72	0.18	0.90	−0.68	−0.82	0.08	0.90	−0.22	0.07	0.29	−0.61
	(−3.98)	(0.41)	(3.69)	(−3.53)	(2.07)	(3.58)	(−1.61)	(−2.28)	(0.31)	(2.06)	(−1.19)	(0.76)	(1.20)	(−1.34)
NEI	−0.30	0.57	0.87	−0.08	0.09	0.17	−0.70	−0.20	0.38	0.59	−0.02	−0.08	−0.06	−0.65
	(−2.01)	(1.73)	(2.55)	(−0.91)	(0.63)	(0.86)	(−2.02)	(−1.19)	(1.17)	(1.70)	(−0.24)	(−0.61)	(−0.31)	(−1.76)
1/FP	−2.21	0.10	2.31	−1.00	0.15	1.15	−1.16	−1.44	0.09	1.53	−0.49	0.01	0.50	−1.03
	(−5.02)	(0.64)	(4.82)	(−2.84)	(1.71)	(2.97)	(−2.72)	(−3.05)	(0.53)	(2.87)	(−1.50)	(0.05)	(1.21)	(−2.21)
1/OS	−1.21	−0.01	1.20	−0.36	0.07	0.43	−0.77	−0.80	0.05	0.84	−0.23	0.11	0.34	−0.50
	(−2.78)	(−0.04)	(2.53)	(−2.01)	(0.95)	(2.05)	(−1.59)	(−2.00)	(0.26)	(1.87)	(−1.23)	(1.31)	(1.49)	(−1.06)
GP	−0.77	0.40	1.17	−0.42	0.26	0.68	−0.48	−0.57	0.33	0.90	−0.39	0.11	0.50	−0.40
	(−2.87)	(2.04)	(3.57)	(−3.16)	(2.01)	(3.42)	(−1.36)	(−2.00)	(1.61)	(2.60)	(−2.87)	(0.70)	(2.29)	(−1.04)
OP	−1.50	−0.03	1.47	−0.70	0.26	0.96	−0.51	−0.84	−0.14	0.70	−0.16	0.07	0.22	−0.48
	(−3.79)	(−0.17)	(3.41)	(−3.07)	(3.16)	(3.88)	(−1.40)	(−2.37)	(−0.72)	(1.77)	(−0.82)	(0.80)	(1.17)	(−1.18)
1/PERF	−1.96	0.21	2.17	−1.10	0.18	1.28	−0.89	−1.27	0.18	1.46	−0.64	0.04	0.68	−0.78
	(−4.71)	(1.25)	(4.79)	(−3.68)	(1.64)	(3.75)	(−1.86)	(3.34)	(1.00)	(3.24)	(−2.17)	(0.30)	(1.80)	(−1.51)
Average	−1.21	0.18	1.39	−0.43	0.17	0.60	−0.79	−0.81	0.16	0.97	−0.18	0.07	0.24	−0.73
	(−6.11)	(1.27)	(5.99)	(−3.23)	(2.44)	(3.55)	(−3.76)	(−4.22)	(1.09)	(4.14)	(−1.30)	(0.77)	(1.21)	(−3.20)

Notes. This table and Table 4 report the value-weighted average returns of portfolios double sorted on media coverage and anomaly. We report the excess returns and CAPM alphas in Table 4 and the alphas of the Fama-French three-factor model and the Fama-French five-factor model in this table. Media coverage is the natural log of one plus the number of news articles published on the Dow Jones newswire in the past month. All portfolios are rebalanced monthly. Average refers to the average return of these 13 anomalies. The sample period is from 2000 to 2018. Monthly returns and alphas are reported in percentages. Newey-West six-lag adjusted *t*-statistics are reported in parentheses.

The magnitude of the alpha difference between stocks with low and high media coverage is both economically large and statistically significant at 0.79% per month (*t*-stat = 3.76). In addition, most of the alpha spread among the firms with low media coverage comes from the short leg of the anomalies. The short leg has an average return of –1.21% per month (*t*-stat = −6.11), whereas the long leg has an average return of merely 0.18% per month (*t*-stat = 1.27). This is consistent with the notion that arbitrage is more limited for overpriced assets because of short-sale impediments, and, thus, overpricing is more prevalent than underpricing. The above evidence is also consistent with the findings in Stambaugh et al. (2012). They find that many anomalies, including the momentum effect and the profitability premium, are due to the extremely low return from the short legs of various long-short strategies following high-sentiment periods, supporting the notion that the short legs are overpriced, especially during high-sentiment periods.

So far, we do not use the Fama-French five-factor adjustment because many of the anomalies are conceptually similar to the RMW factor in Fama-French's five-factor model. Indeed, the underlying anomaly for the RMW factor is operating profit, which is conceptually similar to other profitability measures, such as ROE. Nonetheless, as a robustness check, we still use the Fama-French five-factor model to calculate our abnormal returns, and the results remain similar for our average portfolios. For example, among firms with low media coverage, the average alpha across these anomalies is about 0.97% per month (*t*-stat = 4.14). On the other hand, among firms with high media coverage, the average alpha is only 0.24% per month (*t*-stat = 1.21). The magnitude of the alpha difference between stocks with low and high media coverage is both economically large and statistically significant at 0.73% per month (*t*-stat = 3.20). Again, most of the alpha comes from the short leg of the anomalies.

Our results are quite consistent across the anomalies underlying these prominent factors, as well as the broader set of underreaction-related anomalies. For example, among firms with low media coverage, the Fama-French five-factor alpha spreads for the anomalies underlying PEAD, MOM, ROE, PERF, PMU, and RMW factors are 1.31%, 1.37%, 0.88%, 1.46%, 0.90%, and 0.70%, respectively. On the other hand, among firms with high media coverage, these Fama-French five-factor alpha spreads are only 0.55%, –0.06%, 0.25%, 0.68%, 0.50%, and 0.22%, respectively. In addition, consistent with these factors, the other seven underreaction-related anomalies are also much more pronounced among firms with low media coverage. Overall, among the 13 Fama-French five-factor alpha difference between firms with low media coverage and firms with high media coverage, six of them are significant, and the least insignificant one has a *t*-stat of 1.04.

Instead of using media coverage as a continuous variable, we also use media coverage as a dummy variable as a robustness check. The media dummy has a value of one if there is media coverage for the firm in the previous month. The results based on media dummy variable are reported in Table B5 in the online appendix. Consistent with our prediction, most of the anomalies underlying these factors are significantly stronger among firms without media coverage in the portfolio-formation periods. Among firms without media coverage, the average anomaly raw return spread (the last row) is about 1.16% per month (*t*-stat = 3.50). On the other hand, among firms with media coverage, the average return spread is only 0.43% per month (*t*-stat = 1.63). The magnitude of the difference between stocks without and with media coverage is both economically large and statistically significant at 0.73% per month (*t*-stat = 3.84). The results based on FF3- and FF5-adjusted alphas, reported as Table B5 in the online appendix, yield a similar pattern to that based on raw excess returns.

Note that many anomalies tend to perform better among smaller firms. Thus, to alleviate the concern that our results are just driven by the correlation between our media coverage and firm size, we perform the following additional exercises. We first orthogonalize the original media coverage against firm size by regressing firm-level media coverage onto firm size in the cross-section in each month. Table 6 reports the results based on double sorting on this orthogonalized residual media coverage and anomaly variables. As we can see, for the average portfolio, the return spread difference among firms with low residual media coverage and among firms with high residual media coverage is 0.45% per month (*t*-stat = 2.62), which is more than half of the 0.77% per month difference when size is not controlled for.[13] Given that size itself could be a genuine proxy for investor attention, the above result does not contradict our attention-based interpretation of the anomalies. In addition, in Section 4, we perform a placebo test using overreaction-related anomalies. We find that media coverage exerts an insignificant effect on this set of anomalies. If our results are purely due to stronger anomaly performance among smaller firms and the positive correlation between media coverage and firm size, then media coverage should also exert a significant effect on overreaction-related anomalies.

We also explore the asset-pricing effect of attention on different types of information. In Table B7 in the online appendix, we focus on two types of media: One is the media on insider trading,[14] and the other is the media on technique analysis.[15] We find that among firms without media reporting on insider trading, the average return of these anomalies is about 0.51% per month (*t*-stat = 1.93). On the other hand, among firms with media reporting on insider trading, the average return of these anomalies is only 0.13% per month (*t*-stat = 0.57). The magnitude of the return difference between stocks without and with media reporting on insider trading is both economically large and statistically significant at 0.38% per month (*t*-stat = 3.23). The results are similar for media reporting on technique analysis, albeit in a weaker magnitude. These results suggest that the information on insider trading and technique analysis especially grabs investors' attention, which thus alleviates the initial inattention-induced mispricing in the portfolio-formation period.[16]

In addition, the news data also allow us to explore the heterogeneity among firms that probably get covered intermittently, compared with firms that get covered repeatedly month by month. If it's the attention story, one might be able to infer that the underreaction-related anomalies should be the weakest among firms that get reported on repeatedly, compared with the other group of firms. We thus explore the heterogeneity effect among firms that get covered intermittently, compared with firms that get covered repeatedly month by month. For example, conditional on there being media coverage in month t, we now separate firms into two groups: one without coverage in month $t-1$ and the other with coverage in month $t-1$.[17] We find that the underreaction-related anomalies are indeed weaker among firms that get reported on repeatedly (with an average FF5-adjusted alpha spread of 0.17% per month), compared with the other group of firms (0.76% per month). The spread difference of 0.59% per month is also marginally significant (*t*-stat = 1.74), as shown in Table B8 in the online appendix.

Although we use media coverage as our main attention proxy, we also construct a composite attention index based on individual proxies to perform robustness checks. For example, using this composite index,

Table 6. Control for Size

	Excess return							CAPM alpha						
	Low media			High media			H-L	Low media			High media			H-L
Anomaly	P1	P5	P5–P1	P1	P5	P5–P1	P5–P1	P1	P5	P5–P1	P1	P5	P5–P1	P5–P1
SUE	0.24	0.66	0.42	0.51	0.67	0.16	−0.26	−0.25	0.24	0.49	−0.03	0.20	0.23	−0.26
	(0.58)	(1.83)	(1.86)	(1.14)	(1.71)	(0.67)	(−1.04)	(−1.39)	(1.58)	(2.19)	(−0.14)	(1.57)	(1.04)	(−0.97)
CAR	0.02	0.40	0.38	0.25	0.96	0.71	0.33	−0.51	−0.10	0.41	−0.40	0.37	0.77	0.36
	(0.04)	(0.89)	(1.35)	(0.45)	(1.95)	(2.66)	(0.92)	(−1.91)	(−0.55)	(1.43)	(−1.55)	(1.73)	(2.92)	(0.97)
RE	−0.16	0.67	0.83	0.53	0.52	−0.02	−0.85	−0.73	0.16	0.89	−0.15	0.00	0.15	−0.74
	(−0.29)	(1.34)	(2.46)	(0.89)	(1.07)	(−0.04)	(−2.72)	(−2.52)	(0.76)	(2.69)	(−0.42)	(−0.01)	(0.40)	(−2.34)
MOM	−0.57	0.53	1.10	0.53	0.58	0.05	−1.04	−1.24	0.05	1.30	−0.28	0.09	0.37	−0.92
	(−0.90)	(1.17)	(2.29)	(0.72)	(1.26)	(0.10)	(−2.95)	(−3.59)	(0.23)	(2.84)	(−0.62)	(0.35)	(0.80)	(−2.77)
IndMom	0.19	0.66	0.47	0.61	0.88	0.27	−0.20	−0.30	0.31	0.61	0.06	0.42	0.36	−0.24
	(0.43)	(1.97)	(1.40)	(1.36)	(2.16)	(1.02)	(−0.70)	(−1.39)	(1.66)	(1.87)	(0.26)	(2.01)	(1.37)	(−0.89)
ROE	−0.59	0.64	1.22	0.39	0.66	0.27	−0.95	−1.26	0.23	1.48	−0.38	0.22	0.60	−0.89
	(−0.88)	(1.80)	(2.77)	(0.54)	(1.78)	(0.59)	(−3.25)	(−3.15)	(1.54)	(3.58)	(−1.03)	(1.68)	(1.53)	(−2.97)
ROA	−0.49	0.47	0.96	−0.22	0.66	0.88	−0.08	−1.22	0.07	1.29	−1.03	0.22	1.25	−0.04
	(−0.66)	(1.37)	(1.90)	(−0.28)	(1.80)	(1.68)	(−0.25)	(−2.87)	(0.50)	(2.97)	(−2.37)	(1.61)	(2.95)	(−0.12)
NEI	0.35	0.73	0.38	0.50	0.58	0.07	−0.30	−0.12	0.33	0.45	−0.02	0.16	0.18	−0.27
	(0.89)	(2.04)	(1.91)	(1.12)	(1.50)	(0.31)	(−1.17)	(−0.83)	(1.61)	(2.34)	(−0.10)	(0.84)	(0.80)	(−1.03)
1/FP	−0.62	0.52	1.13	0.24	0.61	0.37	−0.76	−1.44	0.19	1.63	−0.73	0.24	0.97	−0.66
	(−0.74)	(1.84)	(1.71)	(0.27)	(1.89)	(0.56)	(−1.65)	(−3.49)	(1.38)	(3.37)	(−1.36)	(1.95)	(1.75)	(−1.29)
1/OS	−0.10	0.45	0.55	0.50	0.50	0.00	−0.55	−0.75	−0.01	0.73	−0.24	0.02	0.26	−0.48
	(−0.16)	(1.27)	(1.42)	(0.80)	(1.24)	(0.00)	(−1.65)	(−2.52)	(−0.10)	(2.36)	(−0.75)	(0.14)	(0.83)	(−1.34)
GP	0.10	0.84	0.75	0.12	0.82	0.71	−0.04	−0.36	0.47	0.83	−0.48	0.39	0.87	0.04
	(0.2)	(2.66)	(2.18)	(0.22)	(2.04)	(2.22)	(−0.13)	(−1.36)	(2.53)	(2.41)	(−2.01)	(1.75)	(2.84)	(0.11)
OP	−0.74	0.69	1.42	−0.08	0.83	0.91	−0.52	−1.43	0.26	1.69	−0.84	0.39	1.23	−0.45
	(−1.02)	(1.83)	(2.80)	(−0.10)	(2.34)	(1.54)	(−1.52)	(−3.38)	(1.52)	(3.59)	(−1.77)	(2.58)	(2.29)	(−1.31)
1/PERF	−0.78	0.65	1.44	−0.12	0.65	0.76	−0.68	−1.57	0.28	1.85	−1.02	0.24	1.26	−0.59
	(−0.94)	(2.02)	(2.36)	(−0.13)	(1.82)	(1.20)	(−1.82)	(−3.68)	(1.93)	(4.03)	(−1.97)	(1.70)	(2.41)	(−1.50)
Average	−0.24	0.61	0.85	0.29	0.69	0.40	−0.45	−0.86	0.19	1.05	−0.43	0.23	0.65	−0.40
	(−0.43)	(1.75)	(2.96)	(0.47)	(1.80)	(1.28)	(−2.62)	(−3.90)	(1.66)	(4.61)	(−1.54)	(1.82)	(2.57)	(−2.15)

Notes. This table reports the results of sorting on media residual and anomaly in a 5 × 5 way. The media residual is the residual of the cross-sectional regression of media coverage on the log of the market capitalization (both variables are winsorized at the 5% and 95% level). Media coverage is the natural log of one plus the number of news articles published on the Dow Jones newswire in the past month. The excess returns and CAPM alphas are reported. Average refers to the average return of these 13 anomalies. The sample period is from 2000 to 2018. Monthly returns and alphas are reported in percentages. Newey-West six-lag adjusted *t*-statistics are reported in parentheses.

we repeat the double-sorting exercise in Table 4. In Table 7, we find that the CAPM alpha spread for the average anomaly strategy among firms with low investor attention is 1.01% per month, whereas this spread among firms with high investor attention is only 0.37% per month. The spread difference of 0.64% is also statistically significant (t-stat = 3.79).[18] In addition, we also repeat the exercise in Table 6 using a size-orthogonalized attention measure in a similar manner. To save space, we report these results as Table B10 in the online appendix. We find that for the average portfolio, the return spread difference among firms with low residual attention and among firms with high residual attention is 0.47% per month (t-stat = 3.08) when the CAPM alpha is used, which is, again, more than half of the 0.64% per month difference when size is not controlled for. Because this composite attention index is relatively long, we split our sample into pre-2000 and post-2000 subsamples when media coverage is available. To make these two periods comparable, we focus on the period from 1981 to 1999 (pre-2000) and the period from 2000 to 2018 (post-2000) and construct the composite attention index by abnormal trading volume, past return, analyst coverage, mutual fund net flows, absolute value of earnings surprise, and 52-week high.[19] The results reported in Table B11 in the online appendix show that the return difference between low and high attention is slightly larger in the early sample. It is 0.63% in the pre-2000 period and 0.55% in the post-2000 period. This pattern suggests that the attention effect is slightly stronger in the earlier sample relative to the recent sample.

Lastly, we would like to point out that Bouchaud et al. (2019) also study the cross-sectional heterogeneity for the profitability premium. They find that among firms with more sticky analyst expectations, the profitability premium is stronger, suggesting that sticky expectations play a significant role in the observed profitability premium. Notice that limited attention is not the same as sticky expectations. Although sticky expectations could be a result of limited attention, they could

Table 7. Anomaly Returns with Low and High Attention

	Excess return							CAPM alpha						
	Low attention			High attention			H-L	Low attention			High attention			H-L
Anomaly	P1	P5	P5–P1	P1	P5	P5–P1	P5–P1	P1	P5	P5–P1	P1	P5	P5–P1	P5–P1
SUE	0.00	1.00	1.00	0.45	0.99	0.53	−0.46	−0.88	0.14	1.02	−0.10	0.39	0.48	−0.53
	(0.00)	(2.97)	(4.11)	(2.27)	(4.48)	(3.87)	(−1.70)	(−3.88)	(0.64)	(4.19)	(−1.04)	(3.48)	(3.34)	(−1.94)
CAR	−0.26	0.29	0.55	0.44	1.41	0.97	0.41	−1.25	−0.60	0.65	−0.20	0.69	0.89	0.24
	(−0.69)	(0.81)	(3.37)	(1.90)	(4.66)	(4.99)	(1.66)	(−5.01)	(−2.94)	(3.82)	(−1.92)	(4.08)	(4.76)	(0.95)
RE	−0.47	0.48	0.94	0.57	1.11	0.54	−0.40	−1.54	−0.47	1.06	−0.06	0.40	0.46	−0.61
	(−0.97)	(1.21)	(3.18)	(2.65)	(4.13)	(3.14)	(−1.30)	(−4.93)	(−1.75)	(3.58)	(−0.47)	(2.64)	(2.68)	(−1.96)
MOM	−0.89	0.57	1.46	0.47	1.41	0.94	−0.52	−1.76	−0.12	1.63	0.02	0.75	0.74	−0.90
	(−2.04)	(1.87)	(5.66)	(2.47)	(4.31)	(3.62)	(−1.32)	(−6.56)	(−0.73)	(6.93)	(0.18)	(3.75)	(2.99)	(−2.50)
IndMom	−0.27	0.53	0.80	0.39	0.96	0.57	−0.23	−0.99	−0.17	0.82	−0.12	0.52	0.64	−0.18
	(−0.76)	(1.58)	(3.72)	(1.86)	(4.38)	(3.19)	(−1.01)	(−4.65)	(−0.88)	(3.75)	(−1.15)	(3.88)	(3.62)	(−0.77)
ROE	−0.53	0.60	1.13	0.67	0.95	0.28	−0.85	−1.51	−0.26	1.25	−0.04	0.32	0.36	−0.89
	(−1.11)	(1.88)	(3.62)	(2.22)	(4.2)	(1.38)	(−2.79)	(−4.96)	(−1.38)	(4.18)	(−0.21)	(2.84)	(1.77)	(−2.95)
ROA	−0.42	0.75	1.16	0.66	0.84	0.18	−0.98	−1.42	−0.09	1.34	−0.08	0.21	0.3	−1.04
	(−0.88)	(2.54)	(3.63)	(1.99)	(3.63)	(0.83)	(−3.27)	(−4.81)	(−0.47)	(4.47)	(−0.41)	(1.67)	(1.40)	(−3.47)
NEI	0.23	0.57	0.34	0.49	0.85	0.36	0.02	−0.64	−0.26	0.38	−0.07	0.25	0.32	−0.06
	(0.68)	(1.61)	(1.31)	(2.37)	(3.89)	(2.46)	(0.07)	(−3.32)	(−0.95)	(1.37)	(−0.75)	(2.10)	(2.10)	(−0.20)
1/FP	−0.75	0.63	1.38	0.88	0.78	−0.10	−1.48	−1.85	−0.13	1.72	0.04	0.21	0.17	−1.55
	(−1.34)	(2.32)	(3.56)	(2.58)	(3.47)	(−0.49)	(−4.33)	(−4.99)	(−0.86)	(5.09)	(0.18)	(1.75)	(0.83)	(−4.73)
1/OS	−0.46	0.61	1.07	1.03	0.59	−0.44	−1.51	−1.26	−0.08	1.18	0.42	0.11	−0.31	−1.49
	(−1.02)	(2.07)	(3.58)	(3.35)	(2.89)	(−2.18)	(−5.24)	(−4.36)	(−0.46)	(4.21)	(2.10)	(1.21)	(−1.56)	(−5.18)
GP	−0.51	0.52	1.03	0.54	0.88	0.35	−0.68	−1.24	−0.18	1.05	0.08	0.40	0.32	−0.73
	(−1.33)	(1.60)	(4.20)	(2.55)	(4.07)	(2.28)	(−2.49)	(−5.24)	(−0.96)	(4.14)	(0.73)	(3.29)	(2.04)	(−2.62)
OP	−0.37	0.22	0.59	0.86	0.79	−0.06	−0.66	−1.14	−0.49	0.64	0.23	0.32	0.09	−0.55
	(−0.88)	(0.67)	(1.96)	(2.59)	(3.95)	(−0.27)	(−2.19)	(−4.21)	(−2.49)	(2.06)	(1.06)	(3.47)	(0.38)	(−1.80)
1/PERF	−1.04	0.70	1.73	0.41	0.79	0.38	−1.35	−1.85	0.01	1.86	−0.14	0.30	0.44	−1.42
	(−2.26)	(2.33)	(5.32)	(1.53)	(3.59)	(2.23)	(−4.17)	(−6.12)	(0.07)	(5.80)	(−0.93)	(2.62)	(2.48)	(−4.39)
Average	−0.44	0.49	0.93	0.57	0.91	0.35	−0.59	−1.22	−0.21	1.01	0.04	0.41	0.37	−0.64
	(−1.13)	(1.65)	(5.50)	(2.52)	(4.25)	(3.75)	(−3.46)	(−5.57)	(−1.43)	(6.13)	(0.41)	(4.41)	(3.98)	(−3.79)

Notes. This table reports the value-weighted average returns of portfolios double-sorted on composite attention index and anomaly. We report the excess returns and CAPM alphas. Composite attention index is the average of the z-score of the following nine attention-related variables, including abnormal Google search volume, media coverage, abnormal EDGAR downloads, abnormal trading volume, past return, analyst coverage, mutual fund net flow, absolute value of earnings surprise, and 52-week high. All portfolios are rebalanced monthly. Average refers to the average return of these 13 anomalies. The sample period is from 1965 to 2018. Monthly returns and alphas are reported in percentages. Newey-West six-lag adjusted *t*-statistics are reported in parentheses.

also result from other forces, such as anchoring biases. Investors could be fully informed about all the news (i.e., there is unlimited attention), but they could still be subject to anchoring bias, such as placing too much weight on the previous earnings estimation.

In addition, limited attention is also different from conservatism, which could also lead to underreaction to news. Conservatism is the tendency to insufficiently revise one's beliefs when presented with new evidence (e.g., Edwards 1968). Barberis et al. (1998) develop a formal model of conservatism and representativeness, which could lead to both underreaction and overreaction in a unified framework. In general, investors are simultaneously subject to two biases—conservatism and representativeness—and depending on the nature of the news, these two forces will result in different behavior. In the event of intermittent public news, conservatism dominates and leads to initial underreaction, and as the information becomes more consistent over time, representativeness will dominate and induce overreaction. In their model, investors are again fully informed about the news, and they still adjust less, which is distinct from the limited investor attention channel we consider in this paper. Overall, our results show that the anomalies we examine in this paper are at least partially driven by investor limited attention, a concrete channel leading to underreaction.

3.2. Fama-MacBeth Analysis

The evidence based on our double-sorting exercises in the previous section lends support to our conjecture that many of these underreaction-related anomalies are due to limited attention. However, one concern about our portfolio approach is that the anomaly variable spread is also larger among firms with low media coverage, thus leading to a higher return spread among these firms. In addition, taking ROE as an example, behind limited attention, other forces could also potentially be responsible for the different ROE effects across firms with different levels of news coverage.

Our earlier double-sorting exercises cannot explicitly control for other variables that might drive returns, However, it is impractical to sort on three or more variables, as also argued by Grinblatt and Han (2005). Thus, to inspect additional possible mechanisms, we perform a series of Fama and MacBeth (1973) regressions, which allows us to simultaneously control for many confounding effects.

For example, if the lagged ROE characteristic spread is higher among firms with low news coverage, then the higher ROE premium among this group of firms might simply be due to the higher variation in past ROE characteristics, not to the more limited investor attention per se. Below, we use the multivariate Fama and MacBeth (1973) regression to further control for this confounding effect. In particular, we control for beta, size, book-to-market, short-term return, momentum, long-term return, Amihud illiquidity, *IVOL*, institutional ownership, abnormal trading volume, analyst coverage, composite arbitrage cost score, Fama-French 48 industry dummies, the interaction term between anomaly characteristic and size, and the interaction term between anomaly characteristic and institutional ownership. We include media coverage and its interaction with anomaly variables in our series of Fama-MacBeth regressions.

Specifically, we use the following Fama-MacBeth regression to test our hypothesis:

$$R_{i,t} = c_0 + c_1 * Var_{i,t-1} + c_2 * Media_{i,t-1} + c_3 * Var_{i,t-1} * Media_{i,t-1} + Controls_{t-1} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the monthly raw return on stock i, $Var_{i,t-1}$ is the corresponding anomaly variable's group quintile rank, and $Media_{i,t-1}$ is the media coverage's group quintile rank at the portfolio-formation date. *Controls* are *Beta* (CAPM beta estimated by using past 60 months data), *LME* (logarithm of market capitalization in the previous month), *LBM* (logarithm of book equity value at the end of fiscal year $t-1$ divided by the market capitalization at the end of December of year $t-1$), Ret_{-1} (the stock return in the past month), *MOM* (the 11-month cumulative stock returns from month $t-12$ to month $t-2$), $Ret_{-36,-13}$ (the 24-month cumulative stock returns from month $t-36$ to month $t-13$), *ILLIQ* (Amihud (2002) illiquidity), *IVOL* (the residual sum of squares of the Fama-French three-factor model), *Ownership* (the percentage of outstanding shares held by institutional investors), *ABVOL* (the abnormal trading volume), *Analyst* (analyst coverage), *Arbitrage* (composite arbitrage cost score), $Var*LME$ (the interaction term between anomaly variable's group quintile rank and logarithm of market equity), $Var*Ownership$ (the interaction term between anomaly variable's group quintile rank and institutional ownership), and Fama-French 48 industry dummies. To reduce the effect of outliers, we winsorize our independent variables at the 5% and 95% levels. To further alleviate the concern that our results are driven by the correlation between media coverage and firm size, we also control for the interaction term between anomaly variable and firm size.

The regression coefficients on the interaction terms of anomaly variable and media coverage are our main focus. The corresponding *t*-statistics are computed based on Newey and West (1987) robust standard errors. The results based on our portfolio analysis predict that these coefficients should be negative. Table 8 confirms this prediction. We can see that interaction terms are negative for 10 anomalies and are statistically significant for eight of the 13 anomaly variables, confirming the pattern obtained from portfolio analysis.

Given the importance of controlling for the size effect in this study, we also check the robustness of our results and run weighted least-squares regressions by giving more weight to large-cap stocks. In particular, we use log(size) as weight in our regression, and the results are reported in Panel A of Table B12 in the online appendix, which shows that the interaction between media coverage and anomaly variables is negative for 10 anomalies and statistically significant for eight of the 13 anomaly variables. In addition, because the properties of value-weighted returns are dominated by the behavior of a small number of very large (albeit important) firms because of the well-known heavy tails of the size distribution in the U.S. stock market (Zipf 1949), Jensen et al. (2021) propose to cap the firm size at the 80% NYSE breakpoint to alleviate the dominating power of a few extremely large firms. Thus, we also employ their method, and the results are reported in Panel B in Table B12 in the online appendix. We find that the interaction effect between media coverage and anomaly variables is statistically significant for eight of the 13 anomaly variables. Also, our results indicate that the effect of media coverage on traditional underreaction-related anomalies, such as PEAD and PMU, is no longer significant in the past 20 years, but the attention effect is significant for the anomalies underlying prominent factors such as MOM, ROE, RMW and PERF, highlighting the important role of limited attention in these recently proposed, but highly influential, factor models.

In sum, both the double-sorting portfolio approach and Fama-MacBeth regression tests indicate that the broad set of underreaction-related anomalies are much stronger among firms with low media coverage in the portfolio-formation periods. The consistent results across all these anomalies suggest that inattention-induced underreaction is likely to play a significant role in many of these anomalies and, thus, in the corresponding factors.

Table 8. Fama-MacBeth Tests

Variable	*SUE*	*CAR*	*RE*	*MOM*	*IndMom*	*ROE*	*ROA*	*NEI*	*1/FP*	*1/OS*	*GP*	*OP*	*1/PERF*	*Average*
*Var*Media*	0.02	0.06	−0.04	−0.03	0.01	−0.05	−0.05	−0.01	−0.05	−0.05	−0.02	−0.07	−0.06	−0.08
	(1.53)	(4.60)	(−2.49)	(−2.12)	(0.91)	(−3.23)	(−3.08)	(−1.14)	(−3.59)	(−3.28)	(−1.32)	(−4.34)	(−3.47)	(−3.14)
*Var*LME*	−0.06	−0.07	−0.05	−0.00	−0.05	0.02	0.01	−0.04	0.03	0.02	−0.01	0.03	0.01	−0.07
	(−4.72)	(−6.43)	(−2.86)	(−0.04)	(−3.16)	(0.86)	(0.54)	(−3.52)	(1.58)	(1.04)	(−0.66)	(1.70)	(0.28)	(−2.51)
*Var*Ownership*	−0.33	−0.35	−0.19	−0.38	−0.21	−0.59	−0.63	−0.35	−0.62	−0.24	−0.13	−0.34	−0.63	−1.20
	(−3.81)	(−3.78)	(−2.05)	(−3.95)	(−2.28)	(−5.39)	(−5.75)	(−3.92)	(−4.51)	(−2.50)	(−1.63)	(−4.18)	(−5.16)	(−5.75)
Var	0.70	0.66	0.64	0.29	0.86	0.64	0.73	0.73	0.42	0.30	0.43	0.43	0.80	2.18
	(6.63)	(6.67)	(6.55)	(2.80)	(1.79)	(5.19)	(6.01)	(6.28)	(2.95)	(1.96)	(4.33)	(3.05)	(5.37)	(9.29)
Media	0.00	−0.10	0.18	0.16	0.04	0.23	0.22	0.10	0.24	0.24	0.12	0.30	0.25	0.32
	(0.09)	(−2.44)	(3.63)	(2.91)	(0.89)	(3.76)	(3.55)	(2.51)	(3.93)	(3.63)	(2.41)	(4.66)	(3.88)	(3.47)
Beta	−0.06	−0.06	−0.08	−0.06	−0.06	−0.01	0.00	−0.05	−0.07	−0.06	−0.02	−0.01	−0.01	0.02
	(−0.38)	(−0.46)	(−0.53)	(−0.41)	(−0.43)	(−0.04)	(0.03)	(−0.36)	(−0.52)	(−0.43)	(−0.16)	(−0.08)	(−0.07)	(0.12)
LME	−0.11	−0.10	−0.07	−0.30	−0.14	−0.35	−0.34	−0.18	−0.40	−0.38	−0.23	−0.39	−0.34	−0.13
	(−0.70)	(−0.73)	(−0.48)	(−1.76)	(−1.01)	(−1.86)	(−1.78)	(−1.23)	(−2.09)	(−2.08)	(−1.51)	(2.17)	(−1.82)	(−0.64)
LBM	0.13	0.12	0.12	0.12	0.13	0.16	0.14	0.14	0.09	0.09	0.21	0.16	0.11	0.15
	(2.10)	(1.95)	(1.80)	(1.93)	(2.03)	(2.37)	(2.05)	(2.20)	(1.47)	(1.41)	(3.06)	(2.15)	(1.81)	(2.21)
Ret_{-1}	−3.13	−3.56	−2.80	−2.74	−2.78	−2.95	−2.96	−2.92	−2.93	−2.88	−2.89	−2.88	−3.03	−3.27
	(−5.54)	(−6.40)	(−4.29)	(−4.78)	(−4.89)	(−5.18)	(−5.18)	(−5.06)	(−5.20)	(−5.01)	(−5.02)	(−4.96)	(−5.30)	(−5.75)
MOM	−0.51	−0.40	−0.47		−0.34	−0.50	−0.52	−0.53	−0.40	−0.35	−0.40	−0.36	−0.72	−0.92
	(−1.55)	(−1.22)	(−1.34)		(−1.04)	(−1.54)	(−1.60)	(−1.52)	(−1.30)	(−1.07)	(−1.23)	(−1.09)	(−2.30)	(−2.83)
$Ret_{-36,-13}$	−0.06	−0.07	−0.08	−0.06	−0.07	−0.12	−0.14	−0.08	−0.08	−0.09	−0.08	−0.11	−0.12	−0.16
	(−1.14)	(−1.30)	(−1.55)	(−1.18)	(−1.26)	(−2.24)	(−2.60)	(−1.42)	(−1.57)	(−1.78)	(−1.49)	(−1.99)	(−2.36)	(−3.04)
ILLIQ	0.00	−0.02	0.02	−0.01	0.00	0.03	0.03	0.01	0.03	0.03	0.00	0.02	0.04	0.05
	(0.03)	(−0.21)	(0.27)	(−0.08)	(0.03)	(0.32)	(0.40)	(0.12)	(0.33)	(0.31)	(0.01)	(0.29)	(0.51)	(0.54)
IVOL	−24.56	−25.06	−25.88	−26.02	−26.93	−21.99	−20.89	−26.42	−22.35	−24.41	−24.40	−24.16	−18.57	−15.18
	(−3.68)	(−3.76)	(−3.64)	(−4.08)	(−4.13)	(−3.55)	(−3.43)	(−3.94)	(−4.62)	(−4.44)	(−3.86)	(−3.90)	(−3.49)	(−2.60)
Ownership	1.03	1.07	0.64	1.25	0.71	1.77	1.82	0.78	1.89	0.65	0.36	1.03	1.79	3.28
	(2.14)	(2.05)	(1.33)	(2.45)	(1.26)	(2.97)	(3.00)	(1.67)	(2.70)	(1.08)	(0.69)	(1.99)	(2.72)	(3.75)
ABVOL	0.64	0.68	0.66	0.69	0.72	0.65	0.64	0.69	0.68	0.73	0.72	0.70	0.65	0.57
	(4.57)	(4.99)	(4.73)	(5.29)	(5.28)	(5.02)	(4.97)	(5.05)	(5.33)	(5.66)	(5.35)	(5.26)	(5.16)	(4.57)
Analyst	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.02	0.02
	(1.77)	(1.50)	(2.14)	(1.69)	(1.57)	(1.78)	(1.83)	(1.43)	(1.79)	(1.64)	(1.17)	(1.63)	(1.87)	(2.13)
Arbitrage	−0.53	−0.48	−0.28	−0.47	−0.43	−0.70	−0.94	−0.49	−0.83	−0.91	−0.68	−0.49	−1.21	−1.40
	(−0.79)	(−0.74)	(−0.41)	(−0.73)	(−0.66)	(−1.12)	(−1.52)	(−0.75)	(−1.56)	(−1.62)	(−1.06)	(−0.82)	(−2.13)	(−2.32)

Notes. The table reports the results of Fama-MacBeth tests. The dependent variable is the monthly stock return in percentage. The independent variables include the anomaly's group quintile rank (*Var*), the media number's quintile rank (*Media*), the interaction between media number's group quintile rank and the anomaly's group quintile rank (*Var * Media*), the interaction between the log of market capitalization and the anomaly's group quintile rank (*Var * LME*), the interaction between the institutional ownership and the anomaly's group quintile rank (*Var * Ownership*), and control variables (*Beta*, *LME*, *LBM*, Ret_{-1}, *MOM*, $Ret_{-36,-13}$, *ILLIQ*, *IVOL*, *Ownership*, *ABVOL*, *Analyst*, *Arbitrage*, and *Fama-French 48* industry dummies). The table presents the results of Fama-MacBeth tests by employing equal-weighting schemes. We report both the estimated coefficients and the Newey-West six-lag adjusted *t*-statistics (in parentheses).

3.3. Further Evidence from Subsequent Earnings Announcements

Further, if, for whatever reasons, investors underestimate the importance of current news on firms' future profitability, then firms' profitability has systematic expectational errors. Thus, abnormal stock-price movements should be evident around subsequent earnings announcements because of systematic expectational errors. To assess this possibility, we examine stock-price movements and earnings surprises around subsequent earnings announcement dates by following La Porta et al. (1997) and Engelberg et al. (2018), who find that the anomalies tend to perform very well during subsequent earnings announcements. We differ from them by studying both the announcement return differences and the expectation error differences across firms with low media coverage and with high media coverage in the portfolio-formation periods.

If the large anomaly spread among firms with low media coverage is due to mispricing, and if investors update their expectations right after earnings announcements, then firms in the long (short) leg should earn higher (lower) returns around earnings announcement days when investors realize their previous expectation errors. This is because firms in the long (short) leg tend to have higher (lower) earnings surprises on average. Thus, the return spread during announcements should be most pronounced among firms with low media coverage in the portfolio-formation periods. Subsequent quarterly event returns are measured over a $(-1, +1)$ three-day window around announcements during the next quarter after portfolio formation. We obtain quarterly earnings announcement dates from Compustat. For each quarter, we first calculate the three-day buy-and-hold market-adjusted event return for each stock. We then compute value-weighted averages across all stocks within each portfolio as our quarterly event return for this portfolio.

Table 9 reports these results. For 11 of the 13 anomalies, the value-weighted earnings announcement long-short return spreads are higher among firms with low media coverage than among firms with high media coverage. For the average long-short portfolio, the average announcement return is 0.46% among firms with low media coverage and –0.03% among firms with high media coverage. The difference of 0.49% is also statistically significant. The evidence lends support to the view that investors tend to underreact to current news, especially among firms with low media coverage, and limits to arbitrage prevent this underreaction-induced mispricing from being fully corrected by arbitrageurs. We repeat the exercise by replacing earnings announcement returns with SUE. The pattern is similar. In particular, for all 13 anomalies, the value-weighted SUE spreads are higher among firms with low media coverage than among firms with high media coverage. For the average long-short portfolio, the average SUE spread is 0.55% among firms with low media coverage and 0.06% among firms with high media coverage. The difference of 0.49% is also statistically significant, with *t*-stat = 2.21.

In a nutshell, given that there is a consistently stronger subsequent earnings announcement effect among firms with low media coverage, our evidence suggests that investors underreact to the current firm-level news, especially among firms with low media coverage during portfolio-formation periods. The anomalies, such as the ROE premium, earn significant abnormal returns partially because the overpricing (underpricing) for firms with low (high) ROE is corrected during subsequent earnings announcements.

Table 9. Earnings Announcement Surprise with Low and High Media Coverage

	CAR(−1,1)							*SUE*						
	Low media			High media			H-L	Low media			High media			H-L
Anomaly	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1
SUE	−0.01	0.21	0.22	0.13	−0.02	−0.15	−0.37	−0.29	0.01	0.30	0.04	0.06	0.03	−0.27
	(−0.04)	(1.07)	(0.65)	(0.70)	(−0.17)	(−0.53)	(−0.89)	(−1.31)	(0.16)	(1.86)	(2.62)	(4.96)	(2.36)	(−1.78)
CAR	−0.23	−0.12	0.11	0.75	−0.23	−0.98	−1.10	−0.30	0.10	0.40	0.04	0.07	0.03	−0.37
	(−0.81)	(−0.53)	(0.28)	(3.75)	(−1.51)	(−3.83)	(−2.14)	(−1.79)	(2.79)	(2.36)	(2.11)	(4.13)	(1.84)	(−2.31)
RE	−0.20	0.09	0.29	0.01	−0.13	−0.14	−0.43	−0.70	−0.05	0.65	−0.07	0.13	0.20	−0.45
	(−0.79)	(0.47)	(0.93)	(0.06)	(−0.92)	(−0.55)	(−1.04)	(−2.66)	(−0.25)	(3.31)	(−1.24)	(5.92)	(3.40)	(−2.30)
MOM	−0.19	0.16	0.35	0.00	0.13	0.14	−0.22	−0.68	0.06	0.74	−0.03	0.10	0.13	−0.61
	(−0.72)	(0.72)	(0.95)	(−0.01)	(0.98)	(0.52)	(−0.48)	(−1.61)	(1.52)	(1.77)	(−0.62)	(5.02)	(2.43)	(−1.66)
IndMom	0.54	0.40	−0.14	0.00	0.03	0.02	0.16	−0.06	−0.03	0.03	0.06	0.06	0.00	−0.03
	(3.27)	(2.02)	(−0.58)	(0.03)	(0.14)	(0.10)	(0.51)	(−0.76)	(−0.44)	(0.74)	(5.95)	(5.24)	(0.22)	(−0.72)
ROE	−0.56	0.28	0.84	−0.11	0.06	0.17	−0.68	−1.05	0.07	1.12	0.01	0.06	0.05	−1.07
	(−2.48)	(1.34)	(2.57)	(−0.45)	(0.62)	(0.55)	(−1.45)	(−1.77)	(2.11)	(1.97)	(0.29)	(5.30)	(1.66)	(−1.94)
ROA	−0.68	0.14	0.82	−0.02	−0.02	−0.01	−0.83	−0.66	0.06	0.72	−0.02	0.06	0.08	−0.64
	(−2.77)	(0.63)	(3.44)	(−0.05)	(−0.26)	(−0.01)	(−1.73)	(−1.77)	(2.47)	(2.00)	(−0.32)	(5.64)	(1.47)	(−2.04)
NEI	0.28	0.63	0.36	0.05	−0.06	−0.11	−0.47	−0.06	0.09	0.15	0.04	0.06	0.02	−0.13
	(1.00)	(1.69)	(0.88)	(0.38)	(−0.34)	(−0.45)	(−0.98)	(−0.94)	(5.12)	(2.08)	(3.93)	(4.04)	(1.86)	(−1.98)
1/FP	−0.16	0.22	0.37	−0.26	−0.16	0.11	−0.27	−0.93	0.05	0.98	−0.06	0.07	0.13	−0.86
	(−0.47)	(1.13)	(0.92)	(−0.81)	(−1.98)	(0.37)	(−0.60)	(−1.98)	(2.73)	(2.14)	(−0.91)	(6.77)	(2.05)	(−2.10)
1/OS	−0.85	0.50	1.35	−0.25	0.02	0.27	−1.09	−0.32	0.06	0.39	0.03	0.07	0.04	−0.35
	(−3.84)	(2.49)	(4.33)	(−1.40)	(0.18)	(1.33)	(−3.12)	(−1.43)	(3.49)	(1.74)	(1.32)	(6.68)	(1.80)	(−1.61)
GP	0.29	0.14	−0.15	−0.05	0.14	0.18	0.33	−0.07	0.04	0.11	0.04	0.05	0.01	−0.10
	(2.03)	(0.54)	(−0.58)	(−0.43)	(1.17)	(1.07)	(1.18)	(−0.64)	(3.20)	(1.03)	(1.98)	(6.35)	(0.45)	(−1.03)
OP	−0.69	−0.04	0.65	0.09	0.00	−0.09	−0.74	−0.44	−0.02	0.42	0.06	0.05	−0.01	−0.43
	(−3.16)	(−0.17)	(1.96)	(0.37)	(0.03)	(−0.37)	(−1.98)	(−1.48)	(−0.27)	(1.71)	(3.26)	(6.41)	(−0.74)	(−1.81)
1/PERF	−0.77	0.15	0.92	−0.29	−0.09	0.20	−0.71	−1.05	0.08	1.13	−0.06	0.06	0.13	−1.01
	(−1.67)	(0.66)	(1.87)	(−1.22)	(−1.08)	(0.82)	(−1.36)	(−1.91)	(7.06)	(2.06)	(−0.99)	(6.64)	(2.10)	(−2.02)
Average	−0.25	0.21	0.46	0.00	−0.03	−0.03	−0.49	−0.51	0.04	0.55	0.01	0.07	0.06	−0.49
	(−1.59)	(1.26)	(2.39)	(0.03)	(−0.41)	(−0.19)	(−2.02)	(−1.82)	(1.10)	(2.23)	(0.19)	(6.00)	(2.29)	(−2.21)

Notes. This table reports the value-weighted average of the earnings announcement surprise of portfolios double sorted on media and anomaly in each quarter. *CAR*(−1, 1) indicates the buy-and-hold excess return (minus market return) over a three-day window (−1, 1) around the quarterly earnings announcement day. *SUE* indicates the earnings surprise on the quarterly announcement day, calculated as the difference between the EPS and the median value of analysts' forecast over the stock price. The sample period is from 2000 to 2018. Results are reported in percentages. Newey-West six-lag adjusted *t*-statistics are reported in parentheses.

4. Robustness Checks and Alternative Channels

This section provides a few robustness checks and also investigates alternative channels for the underreaction-related anomalies and their corresponding factors. In particular, we investigate whether traditional macroeconomic risk can account for these anomalies.

4.1. A Placebo Test Using Overreaction-Related Anomalies

Most anomalies tend to be more pronounced among small firms, and small firms tend to have less media coverage. Thus, we have used size-orthogonalized media coverage as our robustness test in Table 6. In this subsection, we perform another placebo test using overreaction-related anomalies. If our results are purely due to stronger anomaly performance among smaller firms and the positive correlation between media coverage and firm size, then media coverage should also exert a significant effect on overreaction-related anomalies in the same manner as their effect on underreaction-related anomalies.

We consider a set of anomalies that previous studies tend to attribute to overreaction. In particular, we consider the value-growth anomalies and the investment-based anomalies in Daniel et al. (2020) because earlier studies suggest that these anomalies are more likely to be driven by extrapolation-induced overreaction. For example, De Bondt and Thaler (1985) and Lakonishok et al. (1994) suggest that the long-term reversal effect and the value effect are potentially driven by extrapolation-induced overreaction, respectively. In addition, the investment-based anomalies could also be driven by chief financial officers' (CFOs') extrapolations, as argued by Gennaioli et al. (2016), which has shown that CFOs' expectation is extrapolative, and firms' high past profitability could lead to overinvestment and, thus, lower future returns.

Notice that beyond its link to firm size, it is not clear how media coverage should affect overreaction-related anomalies. For example, early explanations of overreaction-related anomalies, such as the value premium, typically rely on extrapolation. Take the value premium as an example: Extrapolation-based explanations typically ignore the role of limited attention, and they simply assume that attention is homogeneous across firms or investors. However, it is possible that when investors are more attentive, they also have weaker behavioral biases, including extrapolation. In this case, enhanced attention could lead to weaker extrapolation and, thus, weaker mispricing and weaker future profits based on the value strategy. On the other hand, when investors do not pay attention at all, they do not trade, and, thus, the effect of extrapolation is muted. This would imply that higher attention is associated with higher mispricing and, thus, stronger future profits based on the value strategy. Taken together, these two forces combined lead to an ambiguous prediction on the effect of media coverage on overreaction-related anomalies. On the other hand, the effect of limited attention on underreaction-related anomalies is more straightforward. Limited attention alone leads to underreaction to information, and, thus, among firms with lower investor attention, these underreaction-related anomalies should perform better.

Overall, Table 10 shows that media coverage exerts no significant effect on this set of anomalies. More specifically, for the average combination long-short portfolio, the raw return difference among firms with low and high size-orthogonalized media coverage is only 0.09% per month, with t-stat = 0.64. In contrast, this difference is 0.45% per month (t-stat = 2.62) for underreaction-related anomalies. In addition, only one of the 16 overreaction-related anomalies has a significant raw return difference among firms with low and high media coverage. The benchmark-adjusted returns yield a similar pattern. For example, for the average combination long-short portfolio, the return differences among firms with low and high media coverage, after CAPM, Fama-French three-factor, and Fama-French five-factor adjustment, are 0.11% (t-stat = 0.76), 0.14% (t-stat = 0.91), and 0.15% (t-stat = 0.87) per month, respectively, whereas these corresponding numbers are 0.40% (t-stat = 2.15), 0.38% (t-stat = 2.06), and 0.46% (t-stat = 2.24) per month for underreaction-related anomalies.[20] Moreover, only two of the 16 overreaction-related anomalies have a significant CAPM alpha difference among firms with low and high media coverage, with a maximum magnitude of t-stat = 1.94. Overall, we find that media coverage exerts a significant effect only on underreaction-related anomalies, but not on overreaction-related anomalies. Thus, this finding highlights the special role of media coverage as a proxy for attention, beyond its correlation with firm size.

4.2. Link to Limits to Arbitrage

If the anomaly is indeed due to mispricing, then one should expect that the anomalous return spreads should be more pronounced among firms that are more difficult to arbitrage. Pontiff (2006) proposes a simple model, in which a stock's IVOL represents its arbitrage risk. He shows that a higher IVOL implies greater deterrence to price-correcting arbitrage. Thus, we use IVOL as the proxy for limits to arbitrage.

The double-sorting portfolio approach is used to examine how the anomaly returns vary with the severity of limits to arbitrage. Each month, we construct 25 portfolios by first sorting NYSE, AMEX, and NASDAQ stocks (excluding firms with negative book equity value, firms appearing in Compustat for less than two years, and financial firms) into five groups

Table 10. Returns of Overreaction-Related Anomalies with Low and High Media Coverage

	Excess return							CAPM alpha						
	Low media			High media			H-L	Low media			High media			H-L
Anomaly	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1
B/M	0.28	0.97	0.69	0.47	0.88	0.41	−0.28	−0.19	0.59	0.78	−0.07	0.38	0.45	−0.33
	(0.69)	(2.31)	(1.90)	(0.97)	(1.91)	(1.04)	(−0.89)	(−0.94)	(2.14)	(1.87)	(−0.27)	(1.32)	(1.06)	(−1.00)
E/P	0.11	0.68	0.57	0.54	1.11	0.57	0.00	−0.37	0.25	0.62	−0.01	0.65	0.66	0.05
	(0.28)	(1.52)	(1.73)	(1.12)	(2.67)	(1.59)	(0.00)	(−2.27)	(0.78)	(1.75)	(−0.05)	(2.41)	(1.80)	(0.15)
CF/P	0.23	0.86	0.63	0.67	0.85	0.18	−0.45	−0.21	0.49	0.69	0.11	0.35	0.24	−0.45
	(0.70)	(2.25)	(2.05)	(1.33)	(1.84)	(0.46)	(−1.31)	(−1.12)	(1.85)	(1.92)	(0.47)	(1.42)	(0.62)	(−1.25)
NPY	0.01	0.97	0.96	0.59	0.94	0.36	−0.60	−0.53	0.62	1.15	−0.01	0.54	0.55	−0.6
	(0.02)	(2.89)	(2.57)	(1.07)	(2.53)	(1.00)	(−1.91)	(−2.24)	(2.65)	(3.28)	(−0.05)	(2.20)	(1.67)	(−1.94)
1/DUR	−0.09	0.91	1.00	0.05	0.72	0.67	−0.33	−0.67	0.56	1.22	−0.68	0.28	0.96	−0.27
	(−0.17)	(2.32)	(2.21)	(0.07)	(1.80)	(1.27)	(−0.83)	(−2.06)	(2.11)	(2.61)	(−1.87)	(1.25)	(1.99)	(−0.66)
1/AG	0.10	0.86	0.75	0.33	0.58	0.25	−0.51	−0.42	0.40	0.82	−0.25	0.05	0.30	−0.52
	(0.23)	(2.18)	(2.73)	(0.70)	(1.18)	(0.86)	(−1.55)	(−2.62)	(2.02)	(2.96)	(−1.45)	(0.18)	(1.02)	(−1.59)
1/NOA	0.14	0.71	0.56	0.52	0.51	−0.01	−0.57	−0.32	0.24	0.56	0.02	−0.08	−0.11	−0.66
	(0.35)	(1.83)	(2.03)	(1.24)	(0.93)	(−0.04)	(−1.46)	(−2.18)	(1.00)	(1.87)	(0.13)	(−0.34)	(−0.39)	(−1.75)
1/IVA	0.24	0.64	0.40	0.55	0.74	0.19	−0.21	−0.25	0.20	0.45	0.03	0.23	0.20	−0.25
	(0.52)	(1.69)	(1.85)	(1.24)	(1.67)	(0.94)	(−0.82)	(−1.34)	(1.20)	(2.01)	(0.17)	(1.07)	(0.95)	(−0.98)
1/IG	0.22	0.48	0.26	−0.14	0.63	0.77	0.51	−0.30	0.04	0.34	−0.73	0.06	0.79	0.45
	(0.46)	(1.07)	(0.90)	(−0.25)	(1.22)	(2.50)	(1.35)	(−1.44)	(0.15)	(1.17)	(−3.00)	(0.25)	(2.44)	(1.14)
1/IvG	0.43	0.41	−0.02	0.37	0.84	0.46	0.48	−0.05	−0.02	0.03	−0.17	0.28	0.45	0.42
	(1.06)	(1.04)	(−0.09)	(0.79)	(1.80)	(1.79)	(1.53)	(−0.29)	(−0.13)	(0.13)	(−0.78)	(1.28)	(1.75)	(1.31)
1/IvC	0.55	0.48	−0.08	0.42	0.94	0.52	0.60	0.08	0.00	−0.07	−0.10	0.42	0.52	0.59
	(1.38)	(1.09)	(−0.36)	(0.93)	(2.09)	(2.10)	(2.08)	(0.40)	(0.03)	(−0.33)	(−0.48)	(1.72)	(2.08)	(2.03)
1/ACC	0.52	0.04	−0.49	0.41	0.48	0.07	0.55	0.08	−0.49	−0.56	−0.12	−0.16	−0.05	0.52
	(1.27)	(0.08)	(−1.71)	(0.87)	(0.84)	(0.26)	(1.56)	(0.39)	(−2.24)	(−1.91)	(−0.62)	(−0.61)	(−0.17)	(1.37)
1/POA	0.45	0.31	−0.14	0.42	0.84	0.42	0.56	0.00	−0.15	−0.15	−0.12	0.27	0.39	0.54
	(1.09)	(0.79)	(−0.53)	(0.85)	(1.69)	(1.86)	(1.70)	(0.00)	(−0.71)	(−0.53)	(−0.58)	(1.38)	(1.64)	(1.60)
1/PTA	−0.16	0.44	0.60	0.47	0.71	0.24	−0.35	−0.69	−0.08	0.61	−0.11	0.15	0.26	−0.35
	(−0.33)	(0.95)	(2.47)	(0.94)	(1.48)	(1.01)	(−1.07)	(−3.11)	(−0.56)	(2.44)	(−0.50)	(0.80)	(1.04)	(−1.07)
1/NSI	−0.19	0.81	1.00	0.31	0.83	0.53	−0.48	−0.70	0.45	1.15	−0.27	0.40	0.66	−0.49
	(−0.40)	(2.65)	(2.86)	(0.63)	(2.28)	(2.12)	(−1.58)	(−3.36)	(2.34)	(3.57)	(−1.29)	(2.33)	(2.90)	(−1.64)
1/CSI	0.30	1.05	0.75	0.49	0.86	0.37	−0.38	−0.20	0.72	0.92	−0.05	0.45	0.50	−0.43
	(0.69)	(3.48)	(2.41)	(1.09)	(2.52)	(1.45)	(−1.10)	(−0.81)	(3.62)	(3.12)	(−0.19)	(2.47)	(1.95)	(−1.18)
Average	0.20	0.66	0.47	0.40	0.78	0.37	−0.09	−0.30	0.24	0.53	−0.16	0.27	0.42	−0.11
	(0.48)	(1.85)	(3.06)	(0.85)	(1.84)	(2.26)	(−0.64)	(−2.36)	(1.88)	(3.36)	(−0.98)	(1.69)	(2.45)	(−0.76)

Notes. This table reports the results of sorting on media residual and anomaly in a 5 × 5 way. We report the excess returns and CAPM alphas. The media residual is the residual of the cross-sectional regression of the log of one plus the number of news articles on the log of the market capitalization. All portfolios are rebalanced monthly. Average refers to the average portfolio of all anomalies. The sample period is from 2000 to 2018. Monthly returns and alphas are reported in percentages. Newey-West six-lag adjusted *t*-statistics are reported in parentheses.

based on the quintile of the stock's IVOL and then sort stocks within each IVOL quintile into five groups based on the ranked values of our anomaly variables.

Table 11 reports the monthly long-leg, short-leg, and high-minus-low portfolio value-weighted excess returns within the top and bottom IVOL groups and the corresponding *t*-statistics. Besides examining the raw excess portfolio returns, we also investigate whether the spreads can be explained by the Fama and French (2015) five-factor model. If this classic model can capture the cross-sectional variation in stock returns, the intercept from the following regressions should be statistically indistinguishable from zero:

$$R_{i,t} - R_{ft} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + c_i CMA_t + r_i RMW_t + \varepsilon_{i,t}, \quad (2)$$

where $R_{i,t} - R_{ft}$ is the return of portfolio i in excess of the risk-free rate in month t, MKT_t is the excess return of the market value-weighted portfolio, SMB is the return difference between portfolios of small and large stocks, HML is the return difference between portfolios with high and low book-to-market ratios, CMA is the return difference between portfolios with conservative and aggressive investment, and RMW is the return difference between portfolios with robust and weak operating profitability. The intercepts and the *t*-statistics from the above regression are also reported in Table 11.

More specifically, Table 11 reports the results based on double sorting on stock's IVOL and our anomaly variables. As we can see, the profitability spreads are typically smaller in magnitude and less statistically

Table 11. Anomaly Returns in Low and High IVOL Groups

	Excess returns							FF5 alphas						
	Low IVOL			High IVOL			H-L	Low IVOL			High IVOL			H-L
Anomaly	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1	P1	P5	P5−P1	P1	P5	P5−P1	P5−P1
SUE	0.50	0.78	0.28	−0.65	0.82	1.48	1.20	−0.09	0.20	0.29	−1.07	0.20	1.27	0.98
	(3.00)	(4.38)	(2.33)	(−1.62)	(2.07)	(4.99)	(3.90)	(−0.95)	(2.71)	(2.29)	(−4.22)	(0.94)	(4.01)	(2.90)
CAR	0.68	0.77	0.08	−1.02	0.82	1.84	1.75	−0.04	0.18	0.22	−1.44	0.42	1.86	1.64
	(3.63)	(4.12)	(0.74)	(−2.24)	(1.96)	(7.34)	(6.35)	(−0.52)	(1.90)	(1.67)	(−6.62)	(1.99)	(7.00)	(5.52)
RE	0.72	0.86	0.14	−0.72	0.81	1.53	1.39	0.03	0.14	0.11	−1.28	0.45	1.73	1.62
	(3.60)	(4.26)	(0.89)	(−1.47)	(1.73)	(5.05)	(4.78)	(0.21)	(1.02)	(0.55)	(−4.40)	(1.68)	(5.12)	(5.10)
MOM	0.52	0.83	0.31	−1.44	0.23	1.67	1.36	−0.08	0.36	0.43	−1.93	−0.02	1.91	1.47
	(2.49)	(4.24)	(1.57)	(−3.14)	(0.58)	(4.90)	(4.35)	(−0.56)	(3.27)	(1.95)	(−6.41)	(−0.11)	(4.75)	(4.44)
IndMom	0.34	0.65	0.31	−1.24	0.45	1.69	1.38	−0.12	0.16	0.28	−1.89	−0.02	1.87	1.59
	(1.94)	(3.84)	(2.15)	(−3.11)	(1.16)	(6.19)	(5.28)	(−1.27)	(1.58)	(1.72)	(−7.98)	(−0.09)	(6.24)	(5.88)
ROE	0.50	0.74	0.24	−0.42	0.30	0.72	0.48	−0.14	0.10	0.25	−0.85	−0.22	0.63	0.38
	(2.55)	(4.09)	(1.88)	(−0.85)	(0.79)	(2.24)	(1.39)	(−1.50)	(1.49)	(1.95)	(−2.67)	(−1.15)	(1.78)	(1.00)
ROA	0.60	0.76	0.16	−0.68	0.40	1.08	0.92	−0.05	0.17	0.22	−0.95	−0.10	0.85	0.64
	(2.85)	(4.15)	(1.05)	(−1.37)	(1.05)	(3.22)	(2.51)	(−0.49)	(1.81)	(1.41)	(−3.21)	(−0.52)	(2.34)	(1.67)
NEI	0.49	0.74	0.26	−0.57	−0.06	0.51	0.25	−0.13	0.16	0.29	−0.93	−0.76	0.17	−0.13
	(2.96)	(3.97)	(2.26)	(−1.44)	(−0.14)	(1.63)	(0.79)	(−1.79)	(1.68)	(2.48)	(−5.47)	(−2.51)	(0.50)	(−0.37)
1/FP	0.93	0.63	−0.30	−0.85	0.39	1.24	1.54	0.18	0.04	−0.14	−1.51	0.09	1.60	1.74
	(4.13)	(3.45)	(−1.83)	(−1.57)	(1.13)	(3.16)	(4.00)	(1.41)	(0.41)	(−0.70)	(−4.63)	(0.47)	(4.19)	(4.83)
1/OS	0.51	0.51	0.00	−0.39	−0.04	0.36	0.36	−0.08	0.07	0.15	−0.89	−0.41	0.48	0.33
	(2.96)	(2.96)	(−0.01)	(−0.8)	(−0.12)	(1.07)	(0.99)	(−0.88)	(0.92)	(1.24)	(−3.74)	(−2.31)	(1.60)	(0.93)
GP	0.36	0.68	0.32	−0.80	0.19	0.99	0.67	−0.06	0.20	0.26	−1.05	−0.30	0.75	0.49
	(2.18)	(3.83)	(2.15)	(−1.78)	(0.54)	(3.37)	(2.12)	(−0.71)	(1.95)	(1.98)	(−4.86)	(−1.60)	(2.76)	(1.54)
OP	0.28	0.60	0.32	−0.44	−0.07	0.37	0.05	−0.15	0.08	0.23	−0.61	−0.63	−0.02	−0.26
	(1.47)	(3.41)	(2.34)	(−0.95)	(−0.21)	(1.19)	(0.15)	(−1.49)	(1.14)	(1.74)	(−2.44)	(−3.37)	(−0.08)	(−0.75)
1/PERF	0.47	0.66	0.19	−1.50	0.35	1.86	1.66	−0.11	0.21	0.31	−1.91	−0.01	1.90	1.59
	(2.43)	(3.75)	(1.30)	(−3.19)	(0.99)	(6.45)	(5.28)	(−1.04)	(2.29)	(1.98)	(−7.82)	(−0.04)	(6.55)	(5.41)
Average	0.43	0.64	0.21	−0.8	0.29	1.10	0.88	−0.10	0.17	0.27	−1.23	−0.12	1.10	0.83
	(2.54)	(3.86)	(2.29)	(−1.98)	(0.85)	(7.10)	(5.08)	(−1.69)	(2.81)	(2.88)	(−8.24)	(−0.96)	(7.64)	(5.21)

Notes. This table reports the value-weighted average returns of portfolios dependently double-sorted on idiosyncratic volatility (IVOL) and anomaly. The results of excess returns and FF5 alphas are reported. All portfolios are rebalanced monthly. Average refers to the average return of these 13 anomalies. The sample period is from 1976 to 2018 for anomalies using Compustat quarterly data (*SUE*, *CAR*, *ROE*, *ROA*, *NEI*, and *FP*), 1978 to 2018 for anomalies using I/B/E/S annual forecast data (*RE*), and 1965 to 2018 for other anomalies (*MOM*, *IndMom*, *OS*, *GP*, *OP*, and *PERF*). We report the monthly percentile excess returns and alphas and the corresponding Newey-West six-lag adjusted *t*-statistics in parentheses.

significant among low-IVOL firms and highly significant among high-IVOL firms. The spread differences across groups with low and high IVOL are both statistically significant and economically important. For example, the raw momentum return increases from 0.31% among firms with low IVOL to 1.67% among firms with high IVOL. The difference across these two groups is 1.36% per month with *t*-stat of 4.35. The above evidence supports the view that arbitrage costs prevent mispricing from being fully corrected.

Table 11 also examines the Fama-French five-factor model alphas. We can see that the risk-adjusted alphas are generally similar to the raw returns. One concern about our limits to arbitrage proxy is that it might indirectly capture risk. However, in all of our double-sorted portfolios, the portfolio in the short leg among firms with high IVOL actually has negative excess returns. These negative returns make the compensation for risk argument less likely. As a robustness check, we also use institutional ownership and a composite arbitrage cost measure based on seven popular individual measures as our alternative proxies for limits to arbitrage. The pattern remains similar, as reported in Table B14 in the online appendix.

Overall, the above double-sorting portfolio analysis lends consistent support to the hypothesis that the anomaly spreads should be more pronounced among firms with higher limits to arbitrage if mispricing can partially account for these anomalies.

4.3. Business Cycle Variation

We investigate the time-series variation in our anomaly returns in this section. If these anomalous return spreads are driven by systematic macro-related risk, then they should covary with the business cycle. In addition, the anomaly returns should also be predictable by traditional aggregate risk-premium predictors. Thus, we run predictive regressions of the long-short anomaly spreads on lagged macro-related variables. To save space, we report the regression results in Table B15 in the online appendix. We find that very few of these macro-related variables have significant predictive power for anomaly returns. In addition, many coefficients have a sign that is opposite to that predicted. For example, the regression coefficients on the consumption surplus ratio should be negative, because a high consumption surplus ratio implies a lower level of effective risk aversion and, hence, a low long-short portfolio return if the anomalies are driven by systematic risk; however, it is positive for 12 of 13 anomalies. Similarly, the coefficient on the dividend payout ratio (*DE*) should be positive; however, it is negative in all of our predictive regressions.[21]

Furthermore, if the anomaly returns are driven by systematic risk, firms in the long leg should earn lower returns than firms in the short leg during bad times. Figure B1 in the online appendix plots the average long-short anomaly returns from 1965 to 2018 across both recessions and booms. We find that the anomaly spread is mostly positive during recessions. In fact, the correlation between the average long-short returns and the National Bureau of Economic Research recession indicator is 15%, suggesting that the returns are higher during recessions than during booms. Overall, Table B15 and Figure B1 in the online appendix suggest that exposure to standard macro-related risk is not much greater for the firms in the long legs than for the firms in the short legs. Thus, to further examine the underlying risk dynamics of these anomaly-based portfolios, one should probably search for unconventional risk sources, such as preference shocks or investment-specific shocks.

Overall, our predictive regressions fail to identify the link between time variation in the long-short anomaly spreads and business cycle variables. However, because the predictive ability of business cycle variables for the aggregate risk premium is not particularly strong in the first place, one might argue that the test based on our predictive regressions is not particularly powerful. Thus, in the next subsection, to further inspect the role of macroeconomic risk in the underreaction-related anomalies, we study the anomaly return spreads across both macro news announcement dates and nonannouncement dates.

4.4. Anomaly Performance Across Macro News Announcements

In a recent influential paper, Savor and Wilson (2013) find that excess aggregate market returns on prescheduled macro news announcement days are about 10 times larger than those on nonannouncement days. They argue that macro risk is priced in the stock market and that the risk premium is much higher on macro news announcement days. Thus, if our factor premia and anomaly return spreads are due to compensation for macro risk, these premia and spreads should also be larger on macro news announcement days than on nonannouncement days.

In Table 12, we present the average daily stock returns on announcement days and nonannouncement days and their difference for the long-short anomalies underlying these factors, as well as the underreaction-related anomalies. The first row confirms Savor and Wilson's (2013) finding that excess market returns are indeed much higher on macro news announcement days than on nonannouncement days. The rest of the table reports the long-short

Table 12. Returns on Macro Announcement Days and Nonannouncement Days

			Difference			
Variable	Announce	Nonannounce	Raw	CAPM	FF3	FF5
Market	10.23	3.32	6.91			
	(3.68)	(3.67)	(2.56)			
SUE	2.86	1.89	0.97	0.83	0.92	1.60
	(1.84)	(3.38)	(0.64)	(0.55)	(0.63)	(1.12)
CAR	5.07	2.86	2.21	2.29	2.07	1.77
	(3.42)	(4.58)	(1.43)	(1.48)	(1.34)	(1.15)
RE	0.94	3.93	−2.99	−2.67	−1.95	−1.02
	(0.41)	(4.24)	(−1.26)	(−1.12)	(−0.85)	(−0.46)
MOM	9.36	5.07	4.29	4.62	4.57	4.45
	(2.80)	(4.21)	(1.46)	(1.58)	(1.59)	(1.58)
IndMom	4.27	2.49	1.78	2.63	2.78	2.94
	(1.94)	(3.15)	(0.80)	(1.19)	(1.27)	(1.38)
ROE	−2.22	3.40	−5.62	−4.56	−2.37	0.62
	(−1.03)	(3.74)	(−2.63)	(−2.16)	(−1.25)	(0.40)
ROA	−1.64	3.69	−5.33	−3.83	−1.07	2.40
	(−0.65)	(3.51)	(−2.13)	(−1.57)	(−0.49)	(1.37)
NEI	1.91	1.50	0.40	0.15	0.24	1.17
	(1.38)	(2.75)	(0.29)	(0.11)	(0.19)	(0.91)
1/FP	−1.16	4.19	−5.35	−2.65	0.39	3.17
	(−0.30)	(2.73)	(−1.52)	(−0.79)	(0.13)	(1.20)
1/OS	−5.63	3.08	−8.71	−7.97	−4.80	−2.76
	(−2.80)	(3.7)	(−4.36)	(−3.98)	(−3.14)	(−2.08)
GP	−0.06	2.18	−2.24	−2.36	−2.05	−0.36
	(−0.04)	(3.59)	(−1.44)	(−1.52)	(−1.42)	(−0.27)
OP	−5.61	3.23	−8.85	−7.33	−4.02	−0.59
	(−2.16)	(3.41)	(−3.70)	(−3.14)	(−2.07)	(−0.45)
1/PERF	1.16	5.55	−4.39	−2.91	−0.63	1.68
	(0.40)	(5.09)	(−1.63)	(−1.09)	(−0.26)	(0.82)
Average	0.97	3.36	−2.38	−1.67	−0.34	1.09
	(0.65)	(5.75)	(−1.68)	(−1.18)	(−0.27)	(1.04)

Notes. This table shows the returns on macro news announcement days, nonannouncement days, and their difference. Announcement days are those trading days when PPI numbers (CPI numbers before February 1971), employment numbers, and FOMC interest rate decisions are scheduled for release. We test the return difference by adding an announcement dummy in daily-frequency regression ($Ret_t = a + b \times 1_{announce,t} + c \times Controls_t + \epsilon_t$). We conduct the regression without controls (Raw) and conduct the regressions with controls in CAPM, FF3, and FF5 model. The daily returns and the coefficient of announcement dummy (b) are reported in ten-thousandths. Newey-West six-lag adjusted t-statistics are reported in parentheses. The sample period is from 1976 to 2018 for anomalies using Compustat quarterly data (*SUE*, *CAR*, *ROE*, *ROA*, *NEI*, and *FP*), 1978 to 2018 for anomalies using I/B/E/S annual forecast data (*RE*), 2000 to 2018 for media, and 1965 to 2018 for other anomalies (*MOM*, *IndMom*, *OS*, *GP*, *OP*, and *PERF*). Daily returns and alphas are reported in basis points. Newey and West (1987) six-lag adjusted t-statistics are reported in parentheses.

anomaly excess returns. We can see that for most of the long-short anomalies, the return spreads are opposite to those findings based on aggregate market returns, as in Savor and Wilson (2013). More specifically, the daily market excess return is 10.23 basis points on announcement dates, whereas this value is only 3.32 basis points on nonannouncement dates. On the other hand, the average long-short anomaly-based portfolios have a lower return spread on announcement days. The results based on various benchmark-adjusted alphas produce a similar pattern, except those based on the average FF5-adjusted alpha, which has an insignificant *t*-stat.

In sum, we find that the anomaly returns are smaller on announcement days than on nonannouncement days for eight of 13 anomalies, and no one yields a significant positive difference between announcement days and nonannouncement days. Our evidence suggests that macro risk related to interest rates, unemployment, and PPI is unlikely to be the source of the observed factor premia or the abnormally high return of these anomaly strategies.

5. Conclusions

Both the q-theory of investment and standard valuation theory imply that, all else equal, more profitable firms should earn higher expected returns. Thus, the robust-minus-weak factor in the Fama-French five-factor model and the profitability factor in the q-4 factor model tend to be interpreted as risk factors, although these underlying theories are actually agnostic about the economic forces driving the observed profitability premium. On the other hand, related factors, such as PERF and PEAD, are proposed as mispricing or behavioral factors by recent studies. In this paper, we investigate the role of media coverage, and thus investor attention, in these factors and more broadly in underreaction-related anomalies. In particular, we examine how the anomalies underlying these factors vary systematically with media coverage, arbitrage costs, and macroeconomic conditions.

We find that the underlying anomalies of these factors tend to be much more pronounced among firms with low media coverage in the portfolio-formation periods, and most of the factor CAPM alpha spread comes from the short legs of anomalies and from the firms that are difficult to arbitrage. We also find that these factor premia are unlikely to be driven by traditional macroeconomic risk factors. Thus, our evidence indicates that investor inattention, coupled with limits to arbitrage, plays at least some role in these factor premia. Besides the anomalies underlying these prominent factors, we also investigate the behavior of a broader set of underreaction-related anomalies, and a similar and consistent pattern emerges.

Our study does not aim to find complete explanations for each of the anomalies considered. That is, it does not explain why investors do not pay attention to the specific news embedded in these anomaly variables, such as the failure probability. Numerous existing studies explore the individual anomalies in more detail and provide more specifically focused contexts and interpretations. Our intention is to paint the set of anomalies with a broad brush, because our objective is to investigate the implications of the interaction between investor attention and a broad set of anomalies/factors. Our goal is to explore the possibility that investor attention plays a pervasive role in affecting the degree of mispricing that arises in a broad range of specific contexts. Taking into account the fact that these recent anomaly-characteristics-based factor models can successfully account for a broad set of anomalies, our evidence suggests that a common mispricing component, probably due to behavioral biases, such as investor inattention, underlies many seemingly unrelated anomalies. Consequently, incorporating behavioral biases into an otherwise standard investment-based asset-pricing model to explain a broad set of anomalies could be an interesting avenue for future research.

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Endnotes

[1] More concretely, the RMW factor is defined as the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and the CMA factor is defined as the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which Fama and French (2015) label as conservative and aggressive.

[2] The corresponding underlying anomalies are *CAR, MOM, ROE, PERF*, *GP*, and *OP*, respectively.

[3] Note that these are distinct, but related, anomalies. For example, because the ROE factor can help account for many asset-pricing anomalies, it is only natural that this ROE factor is related to other anomalies, such as the post-earnings announcement drift and momentum. Nonetheless, these anomalies are also distinct from each other because the correlations among these anomalies are not very high, as shown in Table B1 in the online appendix.

[4] We acknowledge that we do not include all the anomalies that are potentially driven by underreaction, such as those based on economically linked firms. Prior studies have documented cross-firm return predictability among economically related firms, including firms that are linked along the supply chain (Cohen and Frazzini 2008; Menzly and Ozbas 2010), single-segment and multisegment firms operating in the same industries (Cohen and Lou 2012), firms operating in the same product markets (Hoberg and Phillips 2018), firms with similar technologies (Lee et al. 2019), and firms headquartered in the same geographic regions (Parsons et al. 2020). It is likely that these anomalies are also driven by limited investor attention.

[5] The key here is that the effect of limited attention on overreaction-related anomalies relies on its interaction with another type of bias,

such as extrapolation. In the extreme case, when there is no attention at all, the effect of extrapolation on asset prices is muted, and, thus, the anomalies' return should be weaker among firms with low attention. However, conditional on the case when investors pay some attention, the relation between attention and the degree of extrapolation could be negative, as we discuss in more detail in Section 4.1. This could lead to weaker anomalies' profits among firms with high attention. Together, these two forces could lead to an overall ambiguous effect of limited attention on overreaction-related anomalies.

[6] The EDGAR downloads data are obtained from Ryans' website (http://www.jamesryans.com/). We thank James Ryans for providing data.

[7] We acknowledge that there are other potential attention measures, which are not considered in our paper. These measures include firm advertising expenditures in Lou (2014), Bloomberg search volume in Ben-Rephael et al. (2017), the number of page views of firms' Wikipedia pages in Focke et al. (2020), and so on. In addition, because different individual attention measures could capture different clientele of investor attention, our composite measure can be viewed as a mixture of both retail and institutional attention.

[8] The website address is http://www.hec.unil.ch/agoyal/. We thank Amit Goyal for providing data.

[9] The website address is https://www.sydneyludvigson.com/data-and-appendixes. We thank Sydney Ludvigson for providing data.

[10] In Table B2 in the online appendix, we also report the transition matrix of the media coverage and the time-series average of the cross-sectional persistence of media coverage. For the firms in the top (bottom) coverage group, there is about 50% chance that they will stay in the top (bottom) in the next month. In addition, the time-series average of the cross-sectional persistence is 0.49. Moreover, in Table B3 in the online appendix, we also report the distribution of media coverage across industries. We find that the monthly average number of reports of the firm in each industry varies in a relatively small range, from 3.33 to 7.91.

[11] We report the returns of the period from 2000 to 2018 when media coverage is available to make better subsequent comparisons. In addition, we also report the returns of the period from 1965 to 2018 in Table B1 in the online appendix. Because Jensen et al. (2021) argue that value-weighted returns put too much weight on a few large firms, we also report equally weighted returns and log-size-weighted returns. As we can see, almost all the results are statistically significant.

[12] For our main analysis, we use lag = 6 in Newey-West adjustment. In Table B4 in the online appendix, we use different lags (i.e., lag = 0 or 2), and we find that our results remain robust.

[13] In addition, the pattern is similar when returns are adjusted by the CAPM, Fama-French three-factor model, and Fama-French five-factor model, as reported in Table 6 and in Table B6 in the online appendix.

[14] The media on insider trading is constructed as the collection of RavenPack category items including insider-buy, insider-sell, insider-gift, insider-sell-registration, insider-surrender, insider-trading-lawsuit-defendant, and insider-trading-lawsuit-plaintiff.

[15] The media on technique analysis is constructed as the collection of RavenPack category items including stock-gain, stock-loss, mkt-close-buy-imbalance, mkt-close-sell-imbalance, no-mkt-close-imbalance, mkt-open-sell-imbalance, mkt-open-buy-imbalance, delay-imbalance, buy-imbalance, sell-imbalance, no-imbalance, relative-strength-index, relative-strength-index-overbought, relative-strength-index-oversold, technical-price-level-resistance-bearish, technical-view, technical-view-bearish, technical-view-bullish, technical-view-overbought, and technical-view-oversold.

[16] We also test other types of information, including fundamental information, analyst-rating information, and product information. However, there is no significant difference.

[17] The number of stocks in the intermittent media-coverage group in each month is ranging from seven to 1,360 with a median value of 438. As a result, some portfolios could not be assigned with any stocks in certain months. To make sure that the results are comparable across two groups, we delete the observations in these months. In addition, our results are similar if we retain these months and assign the missing value with zero.

[18] Again, the results are similar when we use the Fama-French three-factor model and the Fama-French five-factor model for benchmark adjustment, as reported in Table B9 in the online appendix.

[19] Different from the previously defined composite attention index, the attention-related variables, such as Google search volume, media coverage, and abnormal EDGAR downloads, are not included, because the data for these variables start after the year of 2000. The pre-2000 sample starts from 1981 because the data of mutual fund net flows start from the second quarter of 1980. By employing this new composite attention index and choosing this sample period, the samples of pre-2000 and post-2000 are completely comparable.

[20] To save space, the results based on the Fama-French three-factor and five-factor models are reported in Table B13 in the online appendix

[21] On the other hand, mispricing-based explanation would imply that the anomaly return spreads should be higher following periods with high sentiment (Stambaugh et al. 2012) and following periods with high dispersion of opinion (Hong and Sraer 2016). In Table B16 in the online appendix, we indeed find supportive evidence.

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