Anchoring and Global Underreaction to Firm-Specific News*

Tobias Kalsbach[†], Steffen Windmueller[†]

This version: Saturday 4^{th} November, 2023

Abstract

This paper examines how the anchoring effect causes investor underreaction to global firm-specific news. Using a high-frequency methodology to identify news events for stocks in 23 developed countries from 2004 to 2021, the results show that investors tend to hold on to their initial beliefs about a stock despite new information. The 52-week high anchor affects the processing of firm-specific news, leading to a distorted belief updating process. Regression analyses indicate that the interaction between firm-specific news return and nearness to the 52-week high is related to a significant risk-adjusted return, providing evidence of investors' distorted belief updating process.

Keywords: Information and Market Efficiency · Belief · Stock-Returns

JEL: G14 · D83 · L14

*We thank Matthias Hanauer, Christoph Kaserer, Lisa Knauer, Laurens Swinkels, and the TUM School of Management for helpful comments.

†Chair of Financial Management and Capital Markets, Technical University of Munich, Arcisstrasse 21, 80333 Munich, Germany, Email: tobias.kalsbach@tum.de.

†Chair of Financial Management and Capital Markets, Technical University of Munich, Arcisstrasse 21, 80333 Munich, Germany, Email: steffen.windmueller@tum.de.

Anchoring and Global Underreaction to Firm-Specific News

This version: Saturday 4$^{\text{th}}$ November, 2023

Abstract

This paper examines how the anchoring effect causes investor underreaction to global firm-specific news. Using a high-frequency methodology to identify news events for stocks in 23 developed countries from 2004 to 2021, the results show that investors tend to hold on to their initial beliefs about a stock despite new information. The 52-week high anchor affects the processing of firm-specific news, leading to a distorted belief updating process. Regression analyses indicate that the interaction between firm-specific news return and nearness to the 52-week high is related to a significant risk-adjusted return, providing evidence of investors' distorted belief updating process.

Keywords: Information and Market Efficiency · Belief · Stock-Returns

JEL: G14 · D83 · L14

1 Introduction

Investor underreaction to the arrival of news has been a long-standing topic in the finance literature. A large body of empirical and theoretical evidence argues that firms' stock prices respond slowly due to investors' behavioral biases. Theoretical literature often suggests that investors' limited attention results in underreaction to the arrival of news.[1] At the same time, empirical evidence supports this limited attention hypothesis by showing that firms' stock prices respond slowly to the arrival of new information.[2] This paper aims to test a novel psychological explanation, the anchoring effect, as an additional explanation for investor underreaction to global firm-specific news measured through the nearness to the 52-week high price.[3] The anchoring effect, as introduced by Tversky and Kahneman (1974), refers to the tendency of investors to stick to their initial beliefs about a stock, even when facing new information, as suggested by Coibion and Gorodnichenko (2015). This psychological barrier can be enforced when investors use the 52-week high as an anchor when making investment decisions. For example, investors influenced by the anchoring effect will not fully adjust their beliefs if the firm experiences the arrival of positive news (negative news) and if the stock price is close to (far from) the 52-week high, leading to a slow stock price response. Following this, our central hypothesis is closely related to the main argument of the anchoring bias literature, namely that investors do not fully incorporate the new information into their beliefs due to the anchoring effect resulting in the predictability of future stock returns (George and Hwang, 2004; Hong et al., 2015; Huang et al., 2021) and earnings surprises (Birru, 2013).

We adopt the high-frequency methodology of Jiang et al. (2021) to identify all unsched-

[1]Several behavioral theories that focus on investors' underreaction to public news have been proposed (Daniel et al., 1998; Hong and Stein, 1999; Hirshleifer et al., 2011; Peng and Xiong, 2006).

[2]Investors limited attention causes an underreact to different information types. The first type is the release of earnings information (cf., Ben-Rephael et al., 2017). The second type covers general news from peer economically linked firms (cf., Ali and Hirshleifer, 2020). The last type covers the underreaction to news-driven returns (cf., Jiang et al., 2021).

[3]The nearness of the firm's stock price or market to its 52-week high comes with a change in investor trading behavior (cf., Huddart et al., 2009). The 52-week is often associated with two different investor biases. The disposition bias causes the sale (buying) of stocks trading at a historical high (low) (Heath et al., 1999; Poteshman and Serbin, 2003). The second bias the nearness to the 52-week high is associated with is the anchoring bias. This bias leads to the investor's underreaction to news (cf., Huang et al., 2021), and helps to explain the stocks momentum anomaly (cf., Hung et al., 2022).

uled and scheduled news events, which allows us to estimate monthly firm-specific news returns. The sample for the empirical analysis is limited to stocks from the developed markets covering 23 global countries from January 2004 to December 2021. We restrict the sample to this period and markets due to the increase in global news coverage starting in 2004 and the technical requirement of the portfolio sort analysis of having a firm-specific news event in the previous month. We begin by forming independent, country-neutrally double-sorted quintile portfolios using the last month's firm-specific news return (FN) and the nearness to the 52-week high ($NEAR$) at the previous month-end as sorting criteria.

The firm-specific news return and the nearness to the 52-week high yield positive and significant risk-adjusted returns, providing out-of-sample evidence for additional countries and an extended sample period. Next, we follow a portfolio strategy utilizing the anchoring bias in combination with the arrival of firm-specific news. The long (short) leg of the strategy incorporates stocks near (far from) their 52-week high and experiencing extremely positive (negative) firm-specific news. The short leg of the strategy yields a monthly average Fama-French-Carhart (1997) four-factor alpha of -0.30% (t=-2.37), whereas the long side earns an alpha of 1.14% (t=9.60). The combined long-short strategy returns an alpha of 1.44% (t=9.37), which provides the first evidence of the investors' distorted belief updating process. It is important to denote that the portfolio with bad news but a near 52-week high as well as the portfolio with very good news but far from the 52-week high both do not yield any significant returns, further underlining our hypothesis that investors only underreact to good (bad) news if the stock price is near (far from) its 52-week high.

To further analyze how the anchoring of investors induced by the 52-week high impacts the processing of the firm-specific news, we follow the innovative decomposition methodology by George et al. (2014). We perform a similar Fama and MacBeth (1973) cross-sectional regression analysis to decompose the returns of the double-sorted portfolios into three independent components. The first component captures the interaction effect between the firm-specific news return and the nearness to the 52-week high and measures the degree to which the 52-week high effect causes the underreaction to the firm-specific news. The second component focuses solely on the pure firm-specific news effect, and the last part yields the return attributable to the pure nearness to the 52-week high effect. The interaction effect yields an average Fama-French-Carhart (1997) four-factor alpha of 1.47% (t=4.67). In contrast, the pure firm-specific news effect and pure 52-week high effect are insignificant, earning a risk-adjusted return of -0.13% (t=-0.66) and 0.10% (t=0.61), respectively. Excluding the interaction effects from the regression results in two positive and significant pure effects with an alpha of 0.68% (t=10.20) in the case of the pure firm-specific news and an alpha of 0.55% (t=3.88) in the case of the pure 52-week high. These results allow us to conclude that the investors' underreaction to the firm-specific news is partially explained by the anchoring bias induced by the nearness to the 52-week high.

Next, we investigate the role of a stock's limits to arbitrage in causing mispricing. Our results provide evidence that firms indeed drive the induced underreaction of investors with high limits to arbitrage. The effect exists among stocks that are smaller in market capitalization, have lower institutional ownership or analyst coverage, have higher idiosyncratic volatility, and have higher transaction costs.

In several robustness tests, we underline the persistence of our results. By applying different factor models, the risk-adjusted returns of the interaction effect, the pure firm-specific news effect, and the 52-week high effect do not change. Additionally, we provide results on six variations of our firm-specific news measure. By limiting the firm-specific news to earnings announcement days, we find that the risk-adjusted return of the interaction effect is reduced and loses its significance, yielding a global alpha of 1.21% (t=1.60) per month. These results are robust across U.S. and non-U.S. firms, indicating that investors quickly incorporate scheduled news into the stock prices. By excluding earnings announcement days, we find that the global four-factor alpha increases to 1.68% (t=5.17) per month. By modeling a slower information diffusion process, the interaction effect in the most efficient stock market, the U.S., becomes insignificant, yielding a monthly return of 0.52% (t=1.19) per month. Further exclusion of macroeconomic announcements and the predictable component from daily returns resulted in a global risk-adjusted return of interaction effect of 1.38% (t=3.86) and 1.32% (t=4.30), respectively. In the last robustness test, we tackle the concern that the 52-week high is just a replacement of the stock's momentum (MOM). Thus, we replace the nearness to the 52-week high with momentum and run a placebo test. In this case, the risk-adjusted return in the Fama-French-Carhart (1997) model is negative and insignificant.

The pure firm-specific news and momentum effects are positive and significant, independent of including or excluding the interaction effect. This provides evidence that the 52-week high is not just another sort on momentum and that the nearness to the 52-week high proxies the investor's underreaction to firm-specific news.

Lastly, we explore how the nearness to the 52-week high distorts the belief-updating process leading to an underreaction. We use analyst recommendation changes as a direct proxy to observe the belief updating process in financial markets. Our results suggest that analysts are indeed influenced by firm-specific news as they change their recommendations after the arrival of news. However, the upgrade (downgrade) is less likely if positive (negative) news arrives at the firm and the underlying stock price is near (far from) the 52-week high. The findings provide evidence for the hypothesis that the belief updating process is distorted and influenced by stock prices' nearness to the 52-week high and the arrival of firm-specific news.

This study adds to understanding investor underreaction in at least four aspects in an international asset pricing context.

First, we contribute to a better understanding of investor underreaction by explicitly using firm-specific news as the cause. Using the novel high-frequency approach introduced in Jiang et al. (2021), we show that investors not only underreact to focal firm news in the U.S. but also in non-U.S. equity markets. In contrast to Huang et al. (2021), who investigate investor underreaction by proxying news with economically-linked, past-month firm momentum, our news measure utilizes firm-specific news of the focal firm. We provide insights into investor underreaction by showing that limits to arbitrage amplify the underreaction potential, i.e., investor underreaction increases with higher limits to arbitrage.

Second, our paper reveals a crucial economic mechanism behind investor underreaction in global equity markets. We show that the underreaction to firm-specific news disappears when controlling for its interaction with investors' anchoring bias. Prior theoretical studies suggest that investors' underreaction to new information, such as earnings news, can be attributed to different psychological biases (Barberis et al., 1998; Daniel et al., 1998) and limits to arbitrage (Shleifer and Vishny, 1997). Empirically, the mispricing caused by the anchoring bias can be partially explained by the firms' exposure to limits to arbitrage (Byun et al., 2020). We explore the economic mechanism causing the underreaction. We, therefore, rely on the anchoring and adjustment hypothesis by showing that professional forecasters (Campbell and Sharpe, 2009; Cen et al., 2013) include the firm-specific news in their recommendation but are affected by the anchoring bias if the stock is near (far from) the 52-week high and positive (negative) news arrives.

Third, we show that unscheduled, firm-specific news drives the anchoring bias effect on investors' underreaction over the subsequent month. Empirical evidence so far suggested that limits to arbitrage are an important driving force behind investors' underreaction to new information on the earnings announcement date (Hung et al., 2015). Moreover, Birru (2013) and George et al. (2014) find that investors' underreaction is driven by scheduled news, respectively, earnings announcements when quantified by price changes over the subsequent days. In contrast, we consider all news releases over the previous month to measure their pricing impact within the current month. Our results on the investors' distorted belief updating process provide strong evidence on a longer-dated, monthly investor underreaction to unscheduled news, indicating that unscheduled news items require more time to be reflected within stock prices.

Fourth, we contribute to the literature on empirical asset pricing for global equity markets by using an international sample and extended metrics. According to Karolyi (2016), most of today's published studies in top finance journals focused on the United States. In this regard, most literature on news-induced momentum (Chan, 2003; Gutierrez and Kelly, 2008; Hillert et al., 2014; Jiang et al., 2021) concentrates solely on the U.S. stock market. Therefore, we add to the ongoing discussion about the investor underreaction hypothesis and its economic channels by providing non-U.S. out-of-sample evidence (Hou et al., 2018) for the anchoring bias and investor underreaction to firm-specific news.

The remainder of the paper is structured as follows: Section 2 defines the main variables and the return decomposition methodology, which allows us to derive the interaction effect and the two pure effects of the firm-specific news and 52-week high. Section 3 introduces the global dataset. Section 4 presents the empirical results on the anchoring effect and the underreaction to firm-specific news. Section 5 concludes.

2 Empirical Strategy

In this section, we present our empirical strategy for measuring how the nearness to the 52-week high distorts the belief-updating process of an investor after the arrival of firm-specific news and explains investor underreaction. In the first subsection, we present the underlying methodology to construct the two required signals, firm-specific news and the nearness to the 52-week high. The second subsection focuses on the decomposition methodology, which allows us to differentiate between the pure effect of firm-specific news, the pure effect of the nearness to the 52-week high, and their interaction effect.

2.1 Firm-specific news and nearness to the 52-week high

This paper adapts the high-frequency decomposition methodology by Jiang et al. (2021) to identify scheduled and unscheduled firm-specific news.[4] We then relate the investor underreaction to firm-specific news to investors' distorted belief updating process, similar to George and Hwang (2004), Birru (2013), and Huang et al. (2021). This distortion is driven by the psychological barrier imposed by the nearness to the 52-week high price. If the current stock price is near the 52-week high and positive firm-specific news arrives at the firm or the price is far from the 52-week high, and negative firm-specific news arrives, investors are not willing to update their beliefs about the firm's fundamentals due to the anchoring effect.

Our measure of firm-specific news combines daily stock returns with firm-specific news events to decompose daily stock returns into news-driven and non-news-driven returns based on market reactions to firm-specific news releases.[5] To calculate the daily firm-specific news returns, we rely on the regular trading hours of the individual stock exchanges a stock is traded on. If the news is released within regular trading hours of day t, the news return

[4]The method of Jiang et al. (2021) has several advantages over other low-frequency news types. One regularly used news type differentiates between cash-flow news and discount-rate news estimated through vector autoregression (Campbell and Shiller, 1988; Campbell, 1991; Vuolteenaho, 2002), implied cost of capital (Chen et al., 2013), and analyst estimations (Easton and Monahan, 2005; Da and Warachka, 2009; Da et al., 2014). Other regression-based news types differentiate between market-wide and firm-specific news (Roll, 1988; Morck et al., 2000) and additionally noise (Brogaard et al., 2022).

[5]In the study of Jiang et al. (2021), the authors use high-frequency, intraday data for U.S. stocks. Due to global data non-availability, we are restricted to daily stock returns. However, within robustness tests, Jiang et al. (2021) show that their high-frequency-based results hold when using daily instead of intraday data to identify firm-specific news returns.

equals the respective daily return. For news occurring after the closing of a stock's main stock market (i.e., an overnight release), at the weekend, or on a holiday, the news is incorporated into the return of the next trading day $t+1$. If no firm-specific news occurs, we declare the return of this day as non-news. We further aggregate the daily firm-specific news returns to a monthly level, similar to the intraday news aggregation to a daily level in Jiang et al. (2021). Suppose there are M trading days per month. Let $fn_{i,t,n}$ be the mth daily news-driven return for stock i in month t, where m = 1,2,...,M, we can compute the monthly firm-specific focal news return ($FN_{i,t}$) as follows:

$$FN_{i,t} = (\prod_{m=1}^{M} 1 + fn_{i,t,m}) - 1 \times 100 \tag{1}$$

To determine the impact of the psychological barrier and the distortion in the belief updating, we need to derive the stock's nearness to the 52-week high. We, therefore, follow George and Hwang (2004) and Windmüller (2022) and define:

$$NEAR_{i,t} = \frac{UP_{i,t}}{\max\limits_{0 \leq d \leq 52} UP_{i,t-d}}, \tag{2}$$

where $UP_{i,t}$ is the unadjusted stock price of stock i at end of the previous week t.

2.2 Decomposition methodology

To shed light on the distortion in the belief-updating process, we follow the methodology proposed by George et al. (2014) and Huang et al. (2021). Therefore, we first sort all stocks that experienced a firm-specific news arrival based on their nearness to the 52-week high and their firm-specific news return into two independent country-neutral quintile portfolios. Afterward, we utilize two different Fama and MacBeth (1973) regressions to decompose the returns of the double-sorted portfolios. In the first regression, we run a monthly stock-level Fama and MacBeth (1973) regression to estimate the two pure effects of firm-specific news and the nearness to the 52-week high as well as the interaction effect of both across the 5x5

= 25 portfolios. The regression model is specified as follows:

$$
\begin{aligned}
R_{i,t+1} = b_0 &+ b_1 FN^5_{i,t} + b_2 FN^4_{i,t} + b_3 FN^2_{i,t} + b_4 FN^1_{i,t} + b_5 NEAR^5_{i,t} + b_6 NEAR^1_{i,t-1} \\
&+ b_7 FN^5_{i,t} \times NEAR^5_{i,t} + b_8 FN^4_{i,t} \times NEAR^5_{i,t} + b_9 FN^2_{i,t} \times NEAR^5_{i,t} \\
&+ b_{10} FN^1_{i,t} \times NEAR^5_{i,t} + b_{11} FN^5_{i,t} \times NEAR^1_{i,t} + b_{12} FN^4_{i,t} \times NEAR^1_{i,t} \\
&+ b_{13} FN^2_{i,t} \times NEAR^1_{i,t} + b_{14} FN^1_{i,t} \times NEAR^1_{i,t} + \epsilon,
\end{aligned} \tag{3}
$$

where $R_{i,t+1}$ is the stock return of firm i in the next month $t+1$, and right-hand-side variables are dummies indicating the quintile ranking of firm i at the end of the month t for FN and $NEAR$. In the second regression, we exclude the interaction effect from the model, leaving us only with the estimation of the two pure effects of firm-specific news and the nearness to the 52-week high:

$$
R_{i,t+1} = b_0 + b_1 FN^5_{i,t} + b_2 FN^4_{i,t} + b_3 FN^2_{i,t} + b_4 FN^1_{i,t} + b_5 NEAR^5_{i,t} + b_6 NEAR^1_{i,t-1} + \epsilon \tag{4}
$$

In Table 1, we describe the methodology by George et al. (2014), and Huang et al. (2021) on how the individual average portfolio return in each of the 5×5 portfolios sorted by the firm-specific news return and the nearness to the 52-week high is decomposed by the regression parameters and the return components. The lowest nearness to the 52-week high (firm-specific news return) quintile is defined as $NEAR1$ ($FN1$), while the highest nearness to the 52-week high (firm-specific news return) quintile is specified as $NEAR5$ ($FN5$). Similar to Huang et al. (2021), we merge the $NEAR2$, $NEAR3$, and $NEAR4$ quintiles into one group (referred to as $NEAR2 \sim 4$ in Table 1) since it is assumed that the nearness to the 52-week high only exists in the two most extreme $NEAR$ portfolios.

[Table 1 about here.]

In Panel A and Panel B of Table 1, we present how the different estimated parameters of Equation 3 and Equation 4 can be combined to derive the respective average portfolio return in each of the portfolios. We further show how the respective portfolio return can be decomposed into four different return components in Panel C and D. The return components are the benchmark return (μ), the returns associated with the 52-week high (H), the returns attributable to the firm-specific news (N), and the returns associated with the interaction between the firm-specific news and nearness of the stock price to the 52-week high (I). The first return component reflects the benchmark portfolio. It is the average return of the stocks in the portfolio with neither extreme firm-specific news returns nor an extreme nearness to the 52-week high. The second return component is solely driven by the stock's nearness to the 52-week high, regardless of the firm-specific news return ranking. Sorting the stocks into quintiles based on their nearness to the 52-week high results in a return component common among the stocks in the same portfolio. Stocks that are far (f) away from the 52-week high are denoted as H_f and are expected to have a negative return, while stocks that are near (n) the 52-week high are denoted as H_n and are expected to have a positive return. To derive the pure 52-week high effect, we build a long-short strategy that relies solely on the return predictability of the nearness to the 52-week high. We, therefore, define the pure 52-week high effect as:

$$\text{Pure 52-week High Effect} = H_n - H_f = b_5 - b_6. \tag{5}$$

The third return component is solely driven by the firm-specific news return, regardless of the firm-specific news return ranking. Sorting the stocks into quintiles based on their firm-specific news return results in a common return component among the stocks in the same portfolio. Following Jiang et al. (2021), do positive firm-specific news returns predict higher future stock returns, and therefore the firm-specific news component increases from the $FN1$ to the $FN5$ quintile. Stocks with extremely bad (bb) firm-specific news returns are denoted as N_{bb} and bad (b) firm-specific news returns are denoted as N_b, whereas good (g) firm-specific news return are denoted as N_g and extremely good (gg) firm-specific news return are denoted as N_{gg}. While extremely bad firm-specific news returns are associated with negative news momentum and therefore expected to have negative returns in the future, are the extremely good firm-specific news return related to positive future returns. To derive the pure firm-specific news return effect, we build a long-short strategy that relies solely on the return predictability of the firm-specific news return. Depending on the assumption that the 52-week high effect moderates the market underreaction to firm-specific news or not, we define pure firm-specific news as:

$$\text{Pure Firm-specific News Effect} = N_{gg} - N_{bb} = (b_1 + b_{11}) - (b_4 + b_{10}), \text{and} \quad (6)$$

$$= b_1 - b_4. \quad (7)$$

The fourth and last return component is associated with having, on the one hand, good firm-specific news about the firm and a stock price near the 52-week high and, on the other hand, experiencing bad firm-specific news while having a stock price that is far from the 52-week high. While the underreaction to the firm-specific news due to the nearness to the 52-week high could also be driven by the less extreme quintiles (e.g., the $FN2$ and $FN4$ quintile) but with a smaller magnitude, we focus our analysis on the most extreme FN and $NEAR$ quintiles. Stocks with extremely bad firm-specific news returns far from the 52-week high are denoted as $I_{bb,f}$, whereas stocks with extremely good firm-specific news returns near the 52-week high are represented as $I_{gg,n}$. Hence, the interaction effect is defined as:

$$\text{Interaction Effect} = I_{gg,n} - I_{bb,f} = (b_7 - b_{11}) - (b_{14} - b_{10}) \quad (8)$$

If investors don't show any issues with their belief updating process after the arrival of good (bad) firm-specific news while having a stock price that is near (far) its 52-week high, the interaction effect's long-short strategy will not yield any additional significant return component. This would point towards the hypothesis that the portfolio returns are entirely attributable to the pure firm-specific news effect and the pure 52-week high effect. On the other hand, if the return of the interaction effect long-short strategy is positive and significant, this would induce that investors are not willing to update their beliefs and hence are underreacting to the good (bad) news if the stock price is near (far from) its 52-week high.

Finally, the time-series average of the pure firm-specific news effect, the pure 52-week high impact, and the interaction effect are computed. The alphas are calculated by regressing the return components on different asset pricing models to further account for risk factors.[6] To

[6]To benchmark the results of the portfolio sorts, we consider various factor models compromised of the following factors: market ($RMRF$), size (SMB), value (HML), profitability (RMW), investment (CMA),

account for serial auto-correlation, we adjust the t-statistics using Newey and West (1987) standard errors with 12 lags.

3 Data and descriptive statistics

This section describes the data sources used to create the data sets for our empirical analyses and the sample selection procedure. Afterward, we summarize the characteristics of the underlying data set.

3.1 Data

To extract firm-specific news of a firm, we use the RavenPack news database similar to Jiang et al. (2021). This database structures all relevant information on news articles from thousands of providers, including Dow Jones Newswires, the Wall Street Journal, and MarketWatch, Barron's, into machine-readable measures.[7] We rely on a comprehensive global sample from the most relevant sources from different news providers and their archives for our analysis.[8] To rank a firm-specific news story about a given firm, we use two relevance scores provided by RavenPack, which range between 0 and 100, and the novelty score, which ranges from 0 to 365 days. The first score is entity relevance and captures how strongly the underlying news refers to a specific company. A value of 0 (100) means that the company is only mentioned passively (actively). The second score relates to the event relevance and indicates where the underlying event is mentioned the first time. A value greater or equal to 90 suggest that the event is prominently placed in the title or headline within a news feed. Last, we filter the news on its event novelty score. The measure indicates how new the

momentum (WML), and liquidity (LIQ). Appendix C provides a detailed description of the factor construction.

[7]Recent studies using this data set comprise Jiang and Sun (2014), Kelley and Tetlock (2017), Ke et al. (2020), and Jiang et al. (2021).

[8]We use every news provider, namely Alliance News, Benzinga Pro, Dow Jones Newswires, Dow Jones Third Party, EDGAR SEC Filings, The Fly, FX Street News and FX Street Economic Calendar, LexisNexis News and Social Media, MT Newswires, and Factset Transcripts. In a subsequent step, we filter out certain unreliable sources for each news provider by relying on the source rank. The highest source rank is 1, classified as 'Fully accountable, reputable and balanced,' followed by rank 2, described as 'Official, reliable and honest.' and rank 3, classified as 'Acknowledged, formal, and credible.' To include only the most reliable sources, we filter out every source ranked below 2.

information contained in the event is compared to previous news. This score specifies how many days have passed since the same event for the given entity was published. For our final sample, we require news stories to have an entity relevance score of 100, an event relevance of 90, and a minimum event novelty score of 1. These filters guarantee that our news sample covers only economically or fundamentally relevant, non-repeated, and, therefore, undisclosed information about a company. We include only firm-specific news, i.e., mergers and acquisitions, analyst ratings, assets, bankruptcy, credit, credit ratings, dividends, earnings, equity actions, labor issues, product services, and revenue from 29 newsgroups. Applying these filters does not introduce any look-ahead bias, as RavenPack assesses all news articles within milliseconds of receipt and immediately sends the resulting data to the users. All information is thus available at the time of news release.

The U.S. and international equities analyses are based on a global sample comprising stock market data from Thomson Reuters Datastream and accounting data from Worldscope. Several static and dynamic screens are applied to ensure that our sample comprises exclusively of common stocks and provides the highest data quality. First, stocks are identified using Thomson Reuters Datastream constituent lists, particularly Worldscope lists, research lists, and — to eliminate survivorship bias — dead lists. Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2017), non-common equity stocks are eliminated through generic and country-specific static screens. Furthermore, several dynamic screens are applied to stock returns and prices to exclude erroneous and illiquid observations. Appendix B.2 and B.3 provide a detailed description of the static and dynamic screens. Finally, stocks must have a market capitalization greater than zero for the previous month, positive book equity, and a return. We limit our-self to countries that are constituents of the MSCI Developed Markets Index in the respective year.[9] To calculate excess returns, we obtain the risk-free rate from Kenneth R. French's homepage.[10]

To combine the stock market data with the firm-specific news, we follow a multi-step procedure to match all corresponding news articles of a corresponding firm to a trading day. In the first step, we determine a firm's Datastream identifier, which corresponds to the

[9]See https://www.msci.com/market-classification for details.
[10]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

RavenPack entity identifier, using the provided ISIN and firm name. In the second step, we map the opening hours of the underlying stock exchange to the merged dataset. Lastly, we allocate the identified firm-specific news based on the opening hours of the respective trading day.

Additionally, we include analyst and institutional ownership data for the stock data. All analyst-related data is collected from Institutional Brokers' Estimate System (I/B/E/S), whereas the Institutional ownership data is from the FactSet Ownership database (formerly LionShares). We merge the I/B/E/S data to our stock sample using the provided I/B/E/S ticker and the FactSet data using the provided ISIN of the firm.

In Table 2, we summarize our sample selection procedure, allowing us to assess whether investors update their beliefs about a stock after the arrival of firm-specific news between January 2004 and December 2021.

[Table 2 about here.]

After applying the different static and dynamic screens, the original sample covers 8.60 million stock-month observations based on 71.113 unique stocks from 53 countries. Due to data availability and quality, we focus our analysis on developed markets reducing the main sample to 24 unique countries. We limit the sample to stocks with daily returns in the previous month to compute the daily news returns. This reduces the sample to 5.31 million stock-month observations. After mapping the firm-specific news events on the daily returns and applying the monthly news aggregation methodology, we end up with 3.34 million stock-month observations, of which 22.3% are from the United States, and 77.7% are from 23 other countries. To analyze investor behavior after the arrival of firm-specific news, we further require the arrival of firm-specific news during the last month. This leads us to a sample size of 1.52 million observations covering 23 countries. To ensure that small and illiquid stocks do not drive our results, we exclude stocks with a market capitalization below its country's 10% quantile each month, in line with Landis and Skouras (2021). We end up with 1.43 million observations. We require a minimum of 25 stocks for each country-month combination to limit the role of idiosyncratic stock price movements and to ensure a minimum level of stock market coverage within each portfolio.Our final sample includes 1.42

million stock-month observations representing 24.337 unique stocks and 23 countries.

3.2 Descriptive statistics

Table 3 provides the summary statistics by country, averaged over time. We provide detailed summary statistics of the developed market countries such as Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, and the United States.

[Table 3 about here.]

On average, we can identify 6.561 stocks per month with a market size of 4.3 billion USD that experience a firm-specific news arrival. The largest market in terms of the number of stocks as well as the market size is the United States, with an average of 2,495 stocks per month and a market size that represent 54.09% of the total market size. The second largest market is Japan, with a maximum of 2,673 stocks per month and coverage of 11.55% of the total market size. While the U.S. market is the largest country in terms of total market size due to its high number of stocks, it is topped with regards to the median size of companies within a country by Austria, Italy, Netherlands, Spain, and Switzerland. We select January 2004 as the start of the sample period due to the broad coverage of firm-specific news events. But several countries like Austria, Denmark, Israel, New Zealand, Norway, and Portugal join the sample at a later stage. In Table 4, we depict the descriptive statistics of the main variables for our final sample. Since our interest is in the behavior of investors after the arrival of firm-specific news in combination with the nearness to the 52-week high, we determine the time-series average of the mean, standard deviation, and quantile breakpoints of the cross-section of the two main variables. We additionally include the share of trading days of observations with a minimum of one firm-specific news story in the month the firm-specific news arrives at the firm.

[Table 4 about here.]

$NEAR$ has a mean of 0.77 and a standard deviation of 0.19, indicating that most firms have stock prices close to the 52-week high. The distribution of $NEAR$ is close to symmetric, with a median of 0.82 and a minimum and maximum of 0.18 and 1.00, respectively. FN, the monthly firm-specific news-driven return, has a mean of 0.81 and a standard deviation of 9.31, indicating significant variation in the firm-specific news return. The distribution of FN is positively skewed, with a median of 0.18 and a minimum and maximum of -20.47 and 29.44, respectively. $FN_{\%}$ has a mean of 0.11 and a standard deviation of 0.09. This implies that if a firm is experiencing a firm-specific news arrival in the month, it is, on average, in the news on two days. The distribution of $FN_{\%}$ is also positively skewed, as the median of 0.09 and a range from 0.05 to 0.48 indicate.

4 Empirical Results

The main objective of this research is to investigate the impact of firm-specific news in conjunction with the proximity to the 52-week high on investor behavior. To achieve this, we utilize firm-specific news returns as the foundation of our analysis. Our methodology involves sorting the firms independently, first by their news returns and then by their proximity to the 52-week high. To verify the validity of the independent double-sort technique, we demonstrate the lack of correlation between the two sorting variables. We then analyze the cross-sectional return patterns among the double-sorted portfolios and examine how the return predictability of news returns is affected by the firm's proximity to the 52-week high.

4.1 Portfolio characteristics

We create double-sorted portfolios by categorizing stocks into country-neutral quintile portfolios based on their firm-specific news returns (FN) and proximity to their 52-week high ($NEAR$) at the previous month-end. This process results in 25 portfolios which are held for one month. In Panels A and B of Table 5, we report the average firm-specific news return and the respective average nearness to the 52-week high by each of the 25 portfolios. In both Panels, $NEAR1$ represents the lowest quintile of $NEAR$, while $NEAR5$ represents the highest quintile of $NEAR$. Analogously, $FN1$ represents the lowest quintile of FN, and $FN5$ represents the highest quintile of FN. In Panel C of Table 5, the correlation between the two main variables is shown.

[Table 5 about here.]

We identify a smaller variation within the $FN1$ quintile among the five $NEAR$ quintiles in the case of firm-specific news returns. The average news return increases from -9.09% in $NEAR1$ to -5.21% in $NEAR5$. For the other four quintiles ($FN2$, $FN3$, $FN4$, $FN5$), the average firm-specific news return does not vary much within the respective FN portfolio and among the different $NEAR$ portfolios. In the case of the highest FN quintile, the average FN in the $NEAR1$ portfolio is 12.03%, whereas the average FN in the $NEAR5$ portfolio is 11.90%. In Panel B, we identify a very similar pattern. Within the lowest $NEAR$ quintile, the average nearness to the 52-week high varies between 0.58 and 0.57 among the five FN quintiles. Among the higher $NEAR$ portfolios, the average nearness to the 52-week high increases to 0.74 in the case of the $NEAR2$ portfolio, 0.83 ($NEAR3$), and 0.90 ($NEAR4$). In the highest $NEAR$ portfolio, the average value varies between 0.96 for the $FN1$ and 0.97 for the $FN5$ portfolio. The correlation statistic in Panel C further reduces the concern that sorting by $NEAR$ could also be a sort by FN.

In the next step, we analyze the return patterns across the 25 portfolios sorted by the firm-specific news returns and the nearness to the 52-week high. We calculate each portfolio's average risk-adjusted monthly equal-weighted returns and report them in Table 6. Panel A reports the excess return; Panel B reports the $CAPM$ alpha, Panel C focuses on the Fama and French (1993a) three-factor alpha ($FF3$), and Panel D uses the Carhart (1997) four-factor model ($FFC4$) as underlying.

[Table 6 about here.]

We will focus our discussion of Table 6 on Panel D, respectively the $FFC4$ alpha, because the other risk-adjusted results are comparable. We first investigate the risk-adjusted portfolio returns of the two original settings (*Orig.*) following George and Hwang (2004) and Jiang et al. (2021). The risk-adjusted portfolio returns increase monotonically from -0.05% (t=-0.70) in the lowest FN to 0.58% (t=6.36) in the highest FN portfolio. A long-short portfolio results in a significant monthly alpha of 0.63% (t=13.74). For the original nearness to the 52-week portfolios, the alpha in the lowest portfolio ($NEAR1$) is equal to 0.02% (t=0.21) and increases to 0.56% (t=7.93) in the $NEAR5$ portfolio. A long-short strategy using the nearness to the 52-week high returns a monthly alpha of 0.53% (t=8.82). Similar to the empirical results of George et al. (2014) and Huang et al. (2021), we also discover that the risk-adjusted portfolio return increases within the respective news portfolio when the $NEAR$ portfolio ranking increases. In the case of the lowest FN portfolio with an average alpha of -0.05% (t=-0.70), the $NEAR1$ portfolio earns a monthly alpha of -0.30% (t=-2.37), which increases to 0.25% (t=1.65) for the $NEAR5$ delivering a long-short return of 0.55% (t=3.42). Moving to the portfolios with high firm-specific news ($FN5$) in the previous month. The firms which are far from the 52-week high ($NEAR1$) earn a monthly risk-adjusted alpha of 0.02% (t=0.10), which increases to 1.14% (t=9.60) for firms close to their 52-week high ($NEAR5$). A long-short portfolio strategy that builds on investors' underreaction due to their belief updating bias earns a monthly risk-adjusted alpha of 1.44% (t=9.37). In the case of the long position, investors do not update their beliefs after the arrival of very good news due to the nearness of the stock to the 52-week high. For the short position, investors are unwilling to update their beliefs after the arrival of very negative news as the stock price is already far-away from its 52-week high. This suggests that very positive stock returns are only predicted by very positive firm-specific news. We find a similar pattern when the stock prices are close to their 52-week high. Low stock returns are predicted by very negative firm-specific news returns when the stock prices are far from their 52-week high.

4.2 Baseline return decomposition results

Next, we apply the return decomposition methodology described in Section 2.2 to disentangle the portfolio returns into the pure effect of the nearness to the 52-week high, the pure firm-specific news effect and their interaction effect and report the results in Table 7. In Panel A of Table 7, we follow Equation 3 and include the interaction effects, whereas, in Panel B, we follow Equation 4 and exclude the interaction effects. If the interaction effect is positive and significant, this indicates that a large part of the portfolio formed on the firm-specific news return is driven by having a stock price close or far from the 52-week high.

[Table 7 about here.]

The interaction effect in Panel A of Table 7 is positive and significant, independent of which factor model is used to calculate the risk-adjusted return component. In column (1), the interaction effect generates an $CAPM$ alpha of 1.51% (t=4.90) per month. By using the Fama and French (1993a) three-factor model in column (2), the risk-adjusted return is also equal to 1.34% (t=4.52) per month, and by additionally including the momentum factor by Carhart (1997) in column (3), the monthly alpha is reduced to 1.47% (t=4.67) per month. In the three previously mentioned setups, the return component driven by the pure firm-specific news effect is negative but insignificant. In the case of the $CAPM$, the risk-adjusted alpha is -0.14% (t=-0.75) per month; for the $FF3$, the alpha amounts to -0.15% (t=-0.78) per month, and in the case of $FFC4$ the alpha is equal to -0.13% (t=-0.66).

The pure firm-specific news effect turns positive and significant by excluding the interaction effect in Panel B. In column (1), the effect amounts to 0.70% (t=10.54) per month; in column (2), the effect is very similar by using $FF3$ as a factor model resulting in an alpha of 0.69% (t=10.49) per month. In column (3), the risk-adjusted return of the pure firm-specific news component amounts to 0.68% (t=10.20) per month when regressing the monthly returns on the Carhart (1997) four-factor model.

The comparison of Panels A and B indicates that positive (negative) firm-specific news results predict high (low) future returns for a company only when the stock prices are close to (far from) the 52-week high. These findings suggest that the nearness to the 52-week high causes investors to react inadequately to firm-specific news, significantly contributing to the firm-specific news phenomenon.

4.3 Results by information environment

Our results suggest that investors cannot update their beliefs about the fair value of a stock after the arrival of good (bad) firm-specific news if the stock price is near (far from) its 52-week high resulting in the mispricing of the stock. Prior studies suggest that investors' underreaction to new information, like earnings news, as well as the anchoring bias, can be partially attributed to the firms' exposure to limits to arbitrage (Shleifer and Vishny, 1997; Hung et al., 2015; Byun et al., 2020). We, therefore, split in Table 8 our primary analysis in chapter 4.2 into two different sub-samples. Panel A covers all stocks with high exposure to limits to arbitrage, while Panel B contains the stock with low limits to arbitrage. We include five different variables that are closely related to limits to arbitrage and are commonly used in the literature (Lam and Wei, 2011). The first two proxies are the stock market capitalization ($Size$) and analyst coverage ($Coverage$), which are a measure of information uncertainty (Hong et al., 2007; Gleason and Lee, 2003; Zhang, 2006). The third proxy is the share of institutional ownership (IO), indicating low short-sale constraints (Nagel, 2005), and the fourth proxy measures through idiosyncratic volatility ($Risk$) potential arbitrage costs (Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Mashruwala et al., 2006; Pontiff, 2006; Duan et al., 2010; McLean, 2010; Stambaugh et al., 2015). The last individual variable is the efficient discrete generalized estimator (TC) as a proxy for potential transaction costs (Ardia et al., 2022).[11] Similar to Smajlbegovic (2019), we add the limits to arbitrage index (LTA) using a linear combination of the ranks of negative market capitalization, negative institutional ownership, negative analysts coverage, idiosyncratic volatility, and transaction costs.

To be able to investigate how the limits to arbitrage affect the three return components, we sort the stocks each month into three country-neutral portfolios based on the underlying limits to arbitrage proxy. Next, due to the reduced number of stocks in each portfolio, we return the decomposition methodology described in Appendix A using 3×3 country-neutral portfolio sorts.

[Table 8 about here.]

The results in Table 8 provide further empirical evidence on the belief updating process of investors. The mispricing effect of investors not being able to update their beliefs about a stock after the arrival of good (bad) firm-specific news and in the case the stock is near (far from) its 52-week high is partially driven by exposure of the stocks to high limits to arbitrage. Each of the six subsamples yields a similar pattern that only the interaction effect in Panel A covering the stocks with high limits to arbitrage is positive and significant. Splitting the sample by size yields an interaction effect for small stocks of 0.96% (t=2.53) per month, whereas large stocks have a monthly alpha of only 0.16% (t=1.02). Using institutional

[11] Ardia et al. (2022) show in their paper that the efficient discrete generalized estimator (EDGE) is superior to other proxies for transaction costs estimators from Roll (1988), Corwin and Schultz (2012), as well as Abdi and Ranaldo (2017) or the Amihud (2002) illiquidity measure.

ownership as the underlying splitting criterion to proxy for the information environment, the alpha of low IO stocks is 0.78% (t=2.27) per month, and of high IO stocks, it is equal to 0.07% (t=0.38). In the case of low analyst coverage, the monthly risk-adjusted return of the interaction effect is 0.87% (t=2.40), whereas, for stocks with high coverage, the alpha is 0.14% (t=0.51). Dividing the sample by idiosyncratic volatility yields a monthly $FF4C$ alpha of 0.60% (t=1.67) for high-risk stocks and 0.24% (t=1.09) for low-risk stocks. The sample split by transaction costs results in a monthly risk-adjusted return of 1.06% (t=3.31) for stocks with high transaction costs and a risk-adjusted return of -0.05% (t=-0.28) per month for stocks with low transaction costs. The linear combination of size, institutional ownership, analyst coverage, risk, and transaction cost underlines the previous results by yielding a monthly alpha of 0.67% (t=2.14) for high limits to arbitrage stocks. In contrast, the low limits to arbitrage stocks are associated with a $FF4C$ alpha of 0.00% (t=0.02).

4.4 Robustness checks

Next, we perform various robustness checks and additional tests to support the findings of the return decomposition. First, we provide further evidence of investor behavior in an out-of-sample application. Second, we use a variety of factor models. Third, we use different definitions of firm-specific news. The last robustness test focuses on a placebo test using the return decomposition based on MOM.

Table 9 splits the sample into two sub-samples. The first sub-sample focuses on the return decomposition in the U.S. and is similar to the analysis in George et al. (2014), Huang et al. (2021), and Jiang et al. (2021). The second sub-sample focuses on a true out-of-sample analysis by excluding the U.S.

[Table 9 about here.]

Even after focusing the return decomposition on the most efficient and mature market, the interaction effect in column (1) remains positive and statistically significant, yielding a risk-adjusted return of 0.61% (t=2.53) per month. Further, excluding the interaction term from the Fama and MacBeth (1973) in column (2) yields positive and statistically significant pure effects. The results of the out-of-sample test in column (3) and column (4) underline the robustness of our results. By comparing the four-factor alpha of the interaction term in column (3) to column (1), we can identify an increase of 1.26 percentage points to 1.87% (t=4.16) per month. The exclusion of the interaction effect in column (4) still yields positive and significant pure effects.

In Table 10, we use a variety of factor models to determine whether the employed factor drives the risk-adjusted returns of the interaction term. More specifically, we extend the Fama and French (1993a) three-factor model with the profitability and investment factor as proposed by Fama and French (2015), resulting in the proposed five-factor model ($FF5$). Further, similar to the model by Carhart (1997), we add momentum to the five-factor model ($FF5C$). To control for liquidity constraints, we employ the four-factor model proposed by Pástor and Stambaugh (2003) by adding the liquidity factor to the Fama and French (1993a) three-factor model (PS). Next, we combine the five-factor model by Fama and French (2015) with the liquidity factor resulting in a six-factor model ($FF5 + LIQ$). The last model augments the $FF5$ with the momentum and liquidity factor resulting in a seven-factor model ($FF5C + LIQ$).

[Table 10 about here.]

In column (1) of Table 10, the risk-adjusted return of the interaction effect slightly increases to 1.61% (t=5.30) per month compared to the three-factor model in Table 7 by adding profitability and investment factor to the factor model. A similar effect can be identified when adding the two additional factors to the Carhart (1997) four-factor model resulting in a monthly alpha of 1.55% (t=5.11). Adding the liquidity factor to the three-factor and five-factor model in column (3) and column (4) yields a monthly risk-adjusted return of 1.53% (t=4.79) and 1.64% (t=5.28), respectively. After controlling for the largest factor model in column (5), the interaction effect remains positive, economically, and statistically significant.

For our third robustness check in Table 11, we add several variations of the previously defined measure of firm-specific news for three samples. The first sample in Panel A uses the entire sample, Panel B focuses on the firms located in the U.S., and Panel C limits the sample to all firms outside of the U.S. The first two alternative measures are related to earnings announcement days (EAD), as these scheduled news events are well-known and followed by investors. To identify these earnings announcement days, we rely on the methodology of Engelberg et al. (2018) by identifying the earnings announcement day as the day with the highest volume within a three-day window around the reported announcement day. To be as precise as possible about the impact of EADs, we define two measures that deviate slightly from our firm-specific news measure. The first measure only includes days with an earnings announcement as a firm-specific news day, while all other days are classified as non-firm-specific news days. The second measure investigates the incremental value of the underlying firm-specific news provider, as we exclude all EADs from the firm-specific news days. The third measure tries to model a slower information diffusion of firm-specific news. If a firm-specific news event occurred on the day t, we additionally classify the next day $t + 1$ as a firm-specific news day. For the next measure, we classify additional events as firm-specific. [12] We exclude the days from the firm-specific news measure on which relevant macroeconomic information is released to exclude the possibility that our results are driven by macroeconomic news. To identify all relevant macro-economic news, we follow Savor and Wilson (2013) by using only the macro announcements that have statistically and economically significant impacts on an individual country's market risk premium.[13] For the last measure, we follow Burt and Hrdlicka (2021) to extract the idiosyncratic news part from daily returns. To decompose the returns into a predictable and unpredictable (idiosyncratic) component, we use an asset pricing model derived from the daily returns of the last 12 months ($t-1$ till $t-12$) and the factor realizations at time t. The estimated parameters enable us to derive the predictable component (ϵ_t), equal to the daily return minus the non-idiosyncratic component. In the final step, we differentiate between idiosyncratic firm-specific and non-firm-specific news returns. For the last measure, we follow Burt and Hrdlicka (2021) to extract the idiosyncratic news part from daily returns.

[Table 11 about here.]

Limiting the firm-specific news to the earnings announcement days in column (1) reduces

[12] These events are 'partnerships,' 'indexes,' 'marketing,' 'regulatory,' 'permits,' 'exploration,' 'commodity-prices,' 'industrial-accidents,' 'business-operations,' 'credit-default-swap,' 'privacy,' and 'ownership.'

[13] Due to the availability we limit our analysis to the following countries: Australia, Canada, France, Germany, Italy, Japan, Netherlands, Norway, New Zealand, Spain, Sweden, Switzerland, United Kingdom, and the United States.

the risk-adjusted return of the interaction effect, loses its significance, and yields an alpha of 1.21% (t=1.60) per month. These results are robust by limiting the sample to only firms located in the U.S. or outside of the U.S. This indicates that investors are paying a lot of attention to these earnings announcement days. Therefore, the news component diffuses very fast into the stock price. A less likely alternative explanation could be that the anchoring effect is not persistent these days, contrary to the results of George et al. (2014). Excluding the earnings announcement days from the firm-specific news return estimation in column (2) increases the four-factor alpha to 1.68% (t=5.17) per month. In column (3), we model a slower information diffusion, resulting in a lower global monthly risk-adjusted return of 1.33% (t=4.90). Limiting the sample to the most efficient stock market, the U.S., the interaction effect even becomes insignificant, yielding an alpha of 0.52% (t=1.19) per month. Including more events in the firm-specific news detection in column (4) further decreases the monthly four-factor alpha to 1.22% (t=3.58). We can identify a similar pattern as in column (3), in which the stocks from outside the U.S. yield a positive and significant alpha. In contrast, the alpha of the U.S. sample is insignificant. This underlines the importance of the event selection by Jiang et al. (2021). Column (5) excludes all the days important macroeconomic announcements are released. The risk-adjusted return of the interaction effect is unaffected by this correction, yielding a global monthly alpha of 1.38% (t=3.86). Similar to column (5), we try to measure the firm-specific news component more exactly by excluding the predictable part from the daily return in column (6). By aggregating the daily idiosyncratic and firm-specific returns, the global risk-adjusted return of interaction effect amounts to 1.32% (t=4.30).

Similar to Huang et al. (2021), our findings may be driven by the momentum effect instead of nearness to the 52-week high since MOM, and $NEAR$ are potentially positively correlated. To rule out this possibility, we address this concern by performing a placebo return decomposition based on MOM instead of $NEAR$ in Table 12.

[Table 12 about here.]

Independent of the underlying factor model is the risk-adjusted return of interaction effect between the firm-specific news and the momentum effect negative and not significant. In column (5), we use the four-factor model as underlying to estimate the alpha of the interaction effect, which amounts to -0.19% (t=-0.62) per month. In contrast, the pure firm-specific news and momentum effects stay significant, yielding a monthly risk-adjusted return of 0.82% (t=4.70) and 0.46% (t=4.62), respectively. Excluding the interaction effect from the regression in column (6) results in a monthly alpha of 0.77% (t=11.10) and 0.39% (t=4.79), when including only the pure firm-specific news effect and the pure momentum effect. This placebo test highlights the uniqueness of the nearness to the 52-week high in explaining the underreaction to the arrival of firm-specific news.

4.5 Analysis of the economic mechanism

In this section, we further investigate the economic mechanism behind the distortion of the belief updating process by combining analyst recommendations revisions and the arrival of firm-specific news. Similar to Huang et al. (2021), we examine analysts' recommendation changes as they provide a direct proxy to observe the belief-updating process of essential information intermediaries in financial markets (Campbell and Sharpe, 2009; Cen et al., 2013). We perform two types of regressions to examine the impact of the nearness to the 52-week high on analyst reactions to the arrival of firm-specific news. The first set of regressions uses an ordered logit, whereas the other set uses an ordinary least squares regression. Each of the regressions uses a binary indicator if the analyst changed his recommendation after the arrival of firm-specific news, the associated firm-specific news return, the nearness to the 52-week high, an interaction of both, as well as several controls resulting in the following equation:

$$RecChange_{i,j} = \beta_1 FN_{i,j} + \beta_2 NEAR_{i,j} + \beta_3 FN_{i,j} \times NEAR_{i,j} + \beta_{1c}\mathbf{C} + \epsilon_{i,j}, \tag{9}$$

where $RecChange_{i,j}$ is recommendation revision event j of firm i. Based on the different Panels in Table 13, the revision event can take different values. In Panel A, the recommendation revision event is defined as $RecChange$. It takes a value of one if the analyst revised his stock recommendation upwards, zero if it is unchanged, and minus one in the case of a downgrade. In Panel B, we regress the independent variables on the dummy $Upgrade$, which equals one for a positive revision and otherwise zero. In Panel C, the dummy *Downgrade* is defined as one in the case of a negative revision and otherwise zero. The regression includes three fundamental variables to understand further analysts' distorted belief updating process. The first variable, FN, is the cumulative firm-specific news return in the 21 trading days before the day of the recommendation change event. The second variable, $NEAR$, is the nearness to the 52-week high at the end of the trading day before the recommendation change, and the last variable, $FN \times NEAR$, is the interaction term between FN and $NEAR$. We include similar control variables as in Huang et al. (2021), determined at the previous month-end before the analyst revision events. The controls cover analyst-based variables like the number of earnings forecast revisions, analyst dispersion, analyst coverage, and standardized unexpected earnings, and further firm-specific controls like firm size, book-to-market ratio, asset growth, and accruals, as well as return-driven controls such as momentum, short-term reversal, and idiosyncratic volatility. We further include industry, year, and country fixed effects in the regression and cluster the standard errors by each firm.

[Table 13 about here.]

We will focus our discussion of Table 13 on columns (1) to (3) of each Panel. Starting with Panel A, the results in column (1) suggest that analysts are more inclined to change their recommendations on a stock in the direction of the firm-specific news event, as evidenced by the positive and significant FN coefficient. This indicates that analysts pay attention to the news and incorporate them into their recommendations. The negative and significant coefficients of the two interaction terms in column (2) and column (3) further indicate that analysts are less likely to upgrade (downgrade) the stock recommendation in response to positive (negative) firm-specific news when the stock price is near (far from) the 52-week high. The results of Panel B and Panel C of Table 13 underline our results by replacing the recommendation change with the two dummy variables *Upgrade* and *Downgarde*. In the case of Panel B, the coefficient of the firm-specific news return is still positive and significant, and the interaction term is negative and significant. These coefficients provide evidence that analysts upgrade their recommendations as soon as positive news arrives at the firm, while they are less likely to do this if the stock price is near its 52-week high. For Panel C, the results are the same as the coefficients are flipped. The negative and significant coefficient of the firm-specific news indicates that if negative firm-specific news arrives, analysts tend to downgrade their recommendations, but due to the positive and significant coefficient on the interaction term are less likely to do this if the stock price is far away from its 52-week high. The results in columns (4) to column (6) of Panel A, B, and C are robust to replacing the ordered logit regression with an ordinary least squares regression. These results provide evidence for our main hypothesis that the distortion of the belief updating process causes an underreaction influenced by the stock prices' nearness to the 52-week high and the arrival of firm-specific news.

5 Conclusion

The paper examines investor underreaction to firm-specific news in global equity markets and tests the anchoring effect as an economic mechanism. The anchoring effect refers to the tendency of investors to cling to their initial beliefs even when facing new information, as reinforced by their use of the 52-week high as an anchor. The paper investigates the central hypothesis that the anchoring effect distorts the investor's belief updating process after the arrival of firm-specific news, resulting in the predictability of future stock returns. The sample for the empirical analysis covers stocks from developed markets across 23 countries from January 2004 to December 2021.

A return decomposition methodology allows us to disentangle the stock return predictability into three components. The first component measures the pure firm-specific news return, the second the pure effect resulting from the stock price nearness to its 52-week high, and the third component the interaction effect between the firm-specific news return and the nearness to its 52-week high. By including all three effects, the interaction effect is positive and significant. In contrast, the pure firm-specific news return turns insignificant compared to the configuration in which only the two pure effects are included in the regression. Our results show that the investors' underreaction to the firm-specific news is at least partially explained by the anchoring bias induced by the nearness to the 52-week high. We also explore how the nearness to the 52-week high distorts the belief-updating process by utilizing analyst recommendation changes, leading to an underreaction. Analysts react to firm-specific news but are less likely to change their recommendation if the stock price is near the 52-week high. Finally, we show that unscheduled, firm-specific news drives the anchoring bias effect on investors' underreaction over the subsequent month. This contrasts previous studies, claiming that investors underreact to scheduled news, such as earnings announcements, over the subsequent days. Our study indicates that investors tend to underreact to unscheduled firm-specific news due to the psychological barrier created by the 52-week high in global equity markets. This offers a fresh perspective on investor underreaction, often attributed solely to investor inattention in the existing literature.

The insights in this paper give rise to future research in at least three dimensions. First, while this study investigates the general underreaction to firm-specific news, one potential avenue for further research could be to explore which news categories are causing the underreaction or by investigating macroeconomic news. Second, while this study focuses on stocks, it could be extended by investigating investors' underreaction within corporate bonds. Third, instead of using the nearness in terms of price, the news decay over time could play another critical role in explaining the underreaction.

Table 1: Specification of return decompostition

This table describes the specification of the return decomposition as in George et al. (2014) and Huang et al. (2021) by regression parameter and return component for the double-sorted firm portfolios by firm-specific news returns (FN) and nearness to the 52-week high ($NEAR$). To form the double-sorting portfolios we sort each month all firms which experienced firm-specific news arrival into independent and country-neutral 5×5 portfolios based on FN in the previous month and $NEAR$ at the previous month-end. Each cell represents a group of stocks with a particular $NEAR$ and FN ranking. Portfolios with $NEAR$ ranked in the $NEAR2$, $NEAR3$, and $NEAR4$ quintiles are combined into one group in the return decomposition. In Panel A (Panel B), we show how the respective portfolio return can be decomposed using the regression parameters from the monthly stock-level Fama and MacBeth (1973) regression as specified in Equation 3 (Equation 4). In Panel C (Panel D), we show how the respective portfolio return can be decomposed into different return components. The return components can be disentangled into the benchmark return (μ), the returns associated with the 52-week high (H), the returns attributable to the firm-specific news (N), and the returns associated with the interaction between the firm-specific news and nearness of the stock price to the 52-week high (I). μ reflects the average return of stocks in the portfolio with neither extreme firm-specific news returns nor an extreme nearness to the 52-week high. H reflects the returns associated with being near (n), middle (m), or far (f) from the 52-week high, regardless of the FN ranking. N reflects the returns associated with having extremely good (gg), good (g), bad (b), or extremely bad (bb) firm-specific news about the firms, regardless of the $NEAR$ ranking. I reflects the returns associated with having both good (bad) firm-specific news about the firm and stock prices near (far from) the 52-week high.

	$FN1$	$FN2$	$FN3$	$FN4$	$FN5$
Panel A: Decomposition by regression parameter *including* the interactions effect					
$NEAR1$	$b_0 + b_4 + b_6 + b_{14}$	$b_0 + b_3 + b_6 + b_{13}$	$b_0 + b_6$	$b_0 + b_2 + b_6 + b_{12}$	$b_0 + b_1 + b_6 + b_{11}$
$NEAR2 \sim 4$	$b_0 + b_4$	$b_0 + b_3$	b_0	$b_0 + b_2$	$b_0 + b_1$
$NEAR5$	$b_0 + b_4 + b_5 + b_{10}$	$b_0 + b_3 + b_5 + b_9$	$b_0 + b_5$	$b_0 + b_2 + b_5 + b_8$	$b_0 + b_1 + b_5 + b_7$
Panel B: Decomposition by regression parameter *excluding* the interactions effect					
$NEAR1$	$b_0 + b_4 + b_6$	$b_0 + b_3 + b_6$	$b_0 + b_6$	$b_0 + b_2 + b_6$	$b_0 + b_1 + b_6$
$NEAR2 \sim 4$	$b_0 + b_4$	$b_0 + b_3$	b_0	$b_0 + b_2$	$b_0 + b_1$
$NEAR5$	$b_0 + b_4 + b_5$	$b_0 + b_3 + b_5$	$b_0 + b_5$	$b_0 + b_2 + b_5$	$b_0 + b_1 + b_5$
Panel C: Decomposition by return component *including* the interactions effect					
$NEAR1$	$\mu + H_f + N_{bb} + I_{bb,f}$	$\mu+H_f+N_b+I_{b,f}$	$\mu + H_f$	$\mu + H_f + N_g$	$\mu + H_f + N_{gg}$
$NEAR2 \sim 4$	$\mu + N_{bb} + I_{bb,m}$	$\mu + N_b + I_{b,m}$	μ	$\mu + N_g + I_{g,m}$	$\mu + N_{gg} + I_{gg,m}$
$NEAR5$	$\mu + H_n + N_{bb}$	$\mu + H_n + N_b$	$\mu + H_n$	$\mu + H_n + N_g + I_{g,n}$	$\mu + H_n + N_{gg} + I_{gg,n}$
Panel D: Decomposition by return component *excluding* the interactions effect					
$NEAR1$	$\mu + H_f + N_{bb}$	$\mu + H_f + N_b$	$\mu + H_f$	$\mu + H_f + N_g$	$\mu + H_f + N_{gg}$
$NEAR2 \sim 4$	$\mu + N_{bb}$	$\mu + N_b$	μ	$\mu + N_g$	$\mu + N_{gg}$
$NEAR5$	$\mu + H_n + N_{bb}$	$\mu + H_n + N_b$	$\mu + H_n$	$\mu + H_n + N_g$	$\mu + H_n + N_{gg}$

Table 2: Sample selection

This table presents the sample selection process for U.S. and Ex-U.S. firms. Column (1) and column (2) cover the number of stock-month observations for the firms located in the U.S. and Ex-U.S. Column (3) and column (4) cover the unique stocks and column (5) the number of unique countries.

	Observation		Firm		Country
	U.S	Ex-U.S.	U.S	Ex-U.S.	Global
	(1)	(2)	(3)	(4)	(5)
... after static and dynamic screens	2157734	6438126	18818	52295	53
... from developed markets	2157734	3290151	18818	27378	24
... with daily stock return	2040066	3270483	18593	27275	24
... with firm-specific news after debut	744563	2597811	6306	18825	23
... with firm-specific news in previous month	549547	965680	6284	18555	23
... with minimum price	539091	891575	6254	18135	23
... with at least 25 stocks per country-month	539091	878159	6254	18083	23
Sample	**539091**	**878159**	**6254**	**18083**	**23**

Table 3: Summary statistics by country

The table presents summary statistics for each of the 22 countries of our sample. Columns (1), (2), (3), and (4), report the total, minimum, mean, and maximum number of firms per country. Columns (5) and (6) state the average mean and median size per country month. Column (7) shows the average total size per country month and column (8) reports these values in percentage of the respective total across countries. The last two columns (9) and (10) report the actual beginning and ending dates during which each country is included in my sample. Size is measured as market capitalization in million USD. The sample period starts in January 2004 and ends in December 2021.

	Number of firms				Size			Date	
	Total	Min	Mean	Max	Mean	Median	%	Start	End
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Australia	2057	78	233	596	3353	396	2.63	04-01	21-12
Austria	74	25	31	42	2571	1498	0.09	04-06	21-12
Belgium	146	25	41	72	5566	864	0.68	04-01	21-12
Canada	3270	348	752	1100	1414	64	3.90	04-01	21-12
Denmark	211	25	49	107	4667	739	0.58	04-03	21-12
Finland	172	25	58	93	3055	574	0.63	04-01	21-12
France	834	90	184	307	7227	770	4.73	04-01	21-12
Germany	844	84	193	335	6257	681	4.17	04-01	21-12
Hong Kong	680	50	132	287	4283	720	1.95	04-01	21-12
Israel	162	25	41	70	2333	656	0.11	10-07	21-12
Italy	444	29	93	196	3437	940	1.07	04-01	21-12
Japan	4503	336	1325	2673	2899	279	11.55	04-01	21-12
Netherlands	147	25	39	69	7798	2187	0.94	04-01	21-12
New Zealand	134	25	34	48	1228	513	0.04	04-03	21-12
Norway	298	26	70	136	2902	383	0.66	04-03	21-12
Portugal	44	26	27	30	2050	408	0.00	06-04	16-06
Singapore	668	31	102	249	2331	365	0.79	04-01	21-12
Spain	241	25	53	99	7843	2303	1.41	04-01	21-12
Sweden	521	37	114	276	2655	378	1.01	04-01	21-12
Switzerland	258	33	68	123	8201	1712	1.95	04-01	21-12
United Kingdom	2128	351	519	721	3435	253	6.90	04-01	21-12
United States	6254	1904	2495	3027	6221	897	54.09	04-01	21-12
Global	24337	4054	6561	8948	4295	424	100.00	04-01	21-12

Table 4: Variable descriptives

The table reports the time-series average of the cross-sectional mean, standard deviation, and quantiles of each variable for the sample of firm-month observations from January 2004 to December 2021. $NEAR$ is the ratio of the unadjusted stock price at the end of the previous month to the past 52-weeks high, as in George and Hwang (2004). FN is the previous monthly firm-specific news from the firm that is based on decomposed daily returns and the RavenPack news database, as in Jiang et al. (2021). $FN_{\%}$ is the average share of news days of the firm in the previous month.

	N	Mean	Std	Min	P1	P25	P50	P75	P99	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$NEAR$	6561.34	0.77	0.19	0.18	0.26	0.67	0.82	0.91	1.00	1.00
FN	6561.34	0.81	9.31	-20.47	-15.55	-2.37	0.18	3.14	20.95	29.44
$FN_{\%}$	6561.34	0.11	0.09	0.05	0.05	0.05	0.09	0.14	0.39	0.48

Table 5: Portfolio characteristics

This table reports the characteristics of the firm portfolios sorted by their firm-specific news return (FN) and their nearness to the 52-week high ($NEAR$). FN is the previous monthly firm-specific news return from the firm that are based on decomposed daily returns and the RavenPack news database, as in Jiang et al. (2021). $NEAR$ is the ratio of the unadjusted stock price at the end of the previous month to the past 52-weeks high, as in George and Hwang (2004). To form the double-sorting portfolios, in each month, the firms are independently sorted into 5 × 5 country-neutral portfolios based on the FN in the previous month and $NEAR$ at the previous month-end. The portfolios are held for one month. Panels A and B report the average FN and $NEAR$ (sorting variables) for each portfolio, respectively. Mean FN in Panel A is shown in percent. Panel C reports the average correlation between $NEAR$ and FN in each month. The sample period is from January 2004 to December 2021.

	(1)	(2)	(3)	(4)	(5)
Panel A: mean FN					
	$FN1$	$FN2$	$FN3$	$FN4$	$FN5$
$NEAR1$	-9.09	-1.65	0.28	2.57	12.03
$NEAR2$	-7.37	-1.64	0.28	2.53	11.09
$NEAR3$	-6.34	-1.61	0.29	2.49	10.57
$NEAR4$	-5.51	-1.57	0.30	2.49	10.32
$NEAR5$	-5.21	-1.46	0.32	2.52	11.90
Panel B: mean $NEAR$					
	$FN1$	$FN2$	$FN3$	$FN4$	$FN5$
$NEAR1$	0.57	0.58	0.58	0.58	0.57
$NEAR2$	0.74	0.74	0.74	0.74	0.74
$NEAR3$	0.83	0.83	0.83	0.83	0.83
$NEAR4$	0.90	0.90	0.90	0.90	0.90
$NEAR5$	0.96	0.97	0.97	0.97	0.97
Panel C: Correlation between FN and $NEAR$					
	FN	PRC			
FN	100.00	12.90			
$NEAR$	12.90	100.00			

Table 6: Portfolio returns

This table reports the performance of the firm portfolios sorted by firm-specific news return (FN) and nearness to the 52-week high ($NEAR$). To form the double-sorting portfolios, each month, the firms are independently sorted into 5×5 country-neutral portfolios based on FN in the previous month and $NEAR$ at the previous month-end. Additionally, we utilize the country-neutral quintile breakpoints to replicate the equal-weighted portfolio returns of the original (*Orig.*) studies (George and Hwang, 2004; Jiang et al., 2021). The equal-weighted portfolios are held for one month and rebalanced every month. This table reports the average monthly excess and risk-adjusted returns of the portfolios. Panel A shows the excess returns. Risk-adjusted returns in Panels A, B, and C are the intercept estimates from the time-series regressions of the monthly excess portfolio returns on market excess return (CAPM), Fama and French (1993b) three factors (FF3), and Carhart (1997) four factors (FFC4), respectively. We report the portfolio holding period returns from January 2004 to December 2021. We compute the original firm-specific news returns and nearness to the 52-weeks high strategy as follows. In each month, we sort the firms into quintiles based on their firm-specific news returns in the previous month or their nearness to the 52-week high. We long the firms in the highest quintile and short the firms in the lowest quintile, and we hold the portfolios for one month. We track the equal-weighted portfolio returns in the holding period. Alphas in this table are reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	Orig.	$FN1$	$FN2$	$FN3$	$FN4$	$FN5$	$FN5-1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Excess Return							
Orig.		0.86	1.03	1.12	1.12	1.50	0.64
		(2.89)	(3.83)	(4.20)	(3.97)	(4.88)	(14.33)
$NEAR1$	1.01	0.71	1.04	1.28	0.97	1.07	0.35
	(2.78)	(1.42)	(2.21)	(2.49)	(2.00)	(2.01)	(3.08)
$NEAR2$	1.00	0.56	0.92	1.07	1.04	1.39	0.84
	(3.16)	(1.30)	(2.28)	(2.57)	(2.40)	(2.88)	(6.21)
$NEAR3$	1.08	0.88	1.02	1.05	1.00	1.46	0.58
	(3.91)	(2.25)	(2.83)	(3.03)	(2.68)	(3.39)	(5.83)
$NEAR4$	1.24	1.03	1.09	1.16	1.28	1.65	0.62
	(4.91)	(2.93)	(3.25)	(3.74)	(3.79)	(4.12)	(5.82)
$NEAR5$	1.31	1.13	1.09	1.07	1.29	1.95	0.82
	(5.59)	(2.83)	(3.48)	(3.71)	(4.22)	(5.53)	(6.19)
$NEAR5-1$	0.29	0.42	0.04	-0.21	0.32	0.89	1.24
	(3.01)	(1.87)	(0.18)	(-0.69)	(1.27)	(3.35)	(5.20)
Panel B: CAPM alpha							
Orig.		-0.04	0.20	0.34	0.27	0.60	0.64
		(-0.41)	(2.30)	(3.34)	(2.92)	(4.96)	(14.15)
$NEAR1$	-0.04	-0.36	-0.00	0.27	-0.08	-0.03	0.33
	(-0.25)	(-1.80)	(-0.01)	(1.13)	(-0.35)	(-0.12)	(3.10)
$NEAR2$	0.05	-0.42	-0.01	0.17	0.10	0.42	0.83
	(0.47)	(-3.02)	(-0.04)	(1.11)	(0.62)	(1.95)	(6.34)
$NEAR3$	0.24	-0.00	0.22	0.27	0.16	0.56	0.56
	(2.70)	(-0.01)	(1.86)	(2.27)	(1.49)	(3.63)	(5.94)
$NEAR4$	0.48	0.24	0.34	0.48	0.52	0.81	0.57
	(6.06)	(2.04)	(3.59)	(4.73)	(5.14)	(5.58)	(5.86)
$NEAR5$	0.63	0.34	0.44	0.49	0.64	1.23	0.89
	(6.99)	(1.98)	(3.30)	(4.34)	(6.28)	(8.51)	(6.86)

Continued on next page

Table 5 continued

	Orig.	*FN*1	*FN*2	*FN*3	*FN*4	*FN*5	$FN5-1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$NEAR5-1$	0.66	0.70	0.44	0.22	0.71	1.25	1.59
	(8.72)	(3.55)	(2.28)	(0.95)	(3.47)	(6.10)	(8.30)
Panel C: FF3 alpha							
Orig.		-0.03	0.22	0.36	0.29	0.61	0.64
		(-0.37)	(3.77)	(5.12)	(4.75)	(6.64)	(14.08)
$NEAR1$	-0.02	-0.34	0.03	0.30	-0.05	-0.02	0.32
	(-0.16)	(-2.61)	(0.19)	(1.71)	(-0.33)	(-0.10)	(3.02)
$NEAR2$	0.08	-0.39	0.02	0.20	0.14	0.43	0.82
	(1.14)	(-4.35)	(0.24)	(1.82)	(1.40)	(2.75)	(6.47)
$NEAR3$	0.27	0.01	0.25	0.30	0.19	0.59	0.58
	(4.37)	(0.14)	(3.00)	(3.90)	(2.45)	(4.71)	(5.98)
$NEAR4$	0.49	0.25	0.36	0.50	0.54	0.82	0.57
	(8.24)	(2.53)	(4.63)	(6.37)	(6.96)	(6.81)	(5.98)
$NEAR5$	0.63	0.34	0.45	0.50	0.65	1.23	0.89
	(8.05)	(2.19)	(3.85)	(5.15)	(7.24)	(9.58)	(6.78)
$NEAR5-1$	0.65	0.68	0.42	0.20	0.70	1.24	1.57
	(9.82)	(3.80)	(2.41)	(1.04)	(4.15)	(6.67)	(8.96)
Panel D: FFC4 alpha							
Orig.		-0.05	0.21	0.36	0.28	0.58	0.63
		(-0.70)	(3.50)	(4.96)	(4.47)	(6.36)	(13.74)
$NEAR1$	0.02	-0.30	0.06	0.34	-0.01	0.02	0.32
	(0.21)	(-2.37)	(0.44)	(1.99)	(-0.04)	(0.10)	(2.93)
$NEAR2$	0.09	-0.39	0.04	0.24	0.16	0.41	0.80
	(1.29)	(-4.36)	(0.44)	(2.15)	(1.53)	(2.63)	(6.54)
$NEAR3$	0.25	-0.01	0.24	0.29	0.18	0.54	0.55
	(4.08)	(-0.07)	(2.87)	(3.77)	(2.37)	(4.35)	(5.66)
$NEAR4$	0.45	0.20	0.32	0.47	0.49	0.77	0.57
	(8.01)	(2.10)	(4.32)	(6.30)	(6.59)	(6.42)	(5.80)
$NEAR5$	0.56	0.25	0.38	0.44	0.57	1.14	0.89
	(7.93)	(1.65)	(3.26)	(4.99)	(6.91)	(9.60)	(6.83)
$NEAR5-1$	0.53	0.55	0.32	0.10	0.57	1.12	1.44
	(8.82)	(3.42)	(1.92)	(0.56)	(4.16)	(6.79)	(9.37)

Table 7: Return decomposition results

This table reports the estimates of the monthly averages for the pure firm-specific news return effect, the pure 52-week high effect, and the interaction effect in the firm-specific news setting. The return decomposition methodology is described in 2.2, and the specifications of the return decomposition are shown in Table 1 and based on the Equation 3 and Equation 4. The pure firm-specific news effect is computed as $N_{gg} - N_{bb}$, where N_{gg} (N_{bb}) is the return associated with having extremely good (bad) firm-specific news regardless of the nearness to the 52-week high. The pure 52-week high effect is computed as $H_n - H_f$, where H_n (H_f) is the return attributable to having stock prices near (far from) the 52-week high regardless of news about the customer firms. The interaction effect is computed as $I_{gg,n} - I_{bb,f}$, where $I_{gg,n}$ ($I_{bb,f}$) is the return associated with having both very good (very bad) firm-specific news and stock prices near (far from) the 52-week high. Panel A reports return decomposition in which interaction effects are included. Panel B reports return decomposition in which interaction effects are excluded. Average monthly $CAPM$ alpha, $FF3$ alpha, and $FFC4$ alpha are the intercepts from time-series regressions of monthly estimates of each effect (e.g., the pure firm-specific news return effect) on market excess returns, Fama and French (1993b) three factors, and Carhart (1997) four factors, respectively. The sample period is from January 2004 to December 2021. Alphas in this table are reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	Alpha		
	CAPM	FF3	FFC4
	(1)	(2)	(3)
Panel A: Interaction effect included			
Interaction	1.51	1.51	1.47
	(4.90)	(4.83)	(4.67)
Pure Firm-specific News	-0.14	-0.15	-0.13
	(-0.75)	(-0.78)	(-0.66)
Pure 52-week High	0.22	0.20	0.10
	(1.01)	(1.10)	(0.61)
Panel B: Interaction effect excluded			
Pure Firm-specific News	0.70	0.69	0.68
	(10.54)	(10.49)	(10.20)
Pure 52-week High	0.68	0.66	0.55
	(3.42)	(3.93)	(3.88)

Table 8: Return decomposition results: subsamples by information environment.

This table reports the results of the return decomposition in subsamples classified by the firms' information environment. The subsamples are generated as follows. Each month firms are sorted equally into country-neutral tercile portfolios based on the underlying firm characteristic available in the previous month. Panel A covers firms in the high limits to arbitrage tercile, whereas Panel B covers firms in the low limits to arbitrage tercile. In column (1), firms are sorted into groups based on market capitalization. In column (2), firms are sorted into groups based on institutional ownership. Institutional ownership are the holdings by all institutional investors as a fraction of the market capitalization. Firms not covered by FactSet are assumed to have zero institutional ownership. In column (3), firms are sorted into groups based on analyst coverage. Analyst coverage is the number of distinct analysts who make fiscal year one earnings forecasts. Firms not covered by I/B/E/S are assumed to have zero analyst coverage. In column (4), firms are sorted into groups based on idiosyncratic volatility. we define idiosyncratic volatility as the standard deviation of the residuals from a regression of excess returns on a local Fama and French (1993b) three-factor model. We use one month of daily data and require at least fifteen non-missing observations. In column (5), firms are sorted into groups based on transaction cost. To estimate transaction cost, we compute for each stock and month the efficient discrete generalized estimator (EDGE) of the bid-ask spread, proposed by Ardia et al. (2022). In column (6), firms are sorted into groups based on the ranked average among the five information environment variables. Within each subsample, we sort the firms into country-neutral 3×3 portfolios based on FN and $NEAR$ and conduct a return decomposition using the methodology described in Appendix B. The sample period is from January 2004 to December 2021. FFC4 Alpha in this table is reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	FF4C Alpha					
	Size	IO	Coverage	Risk	TC	LTA
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High limits to abitrage						
	Small	Low	Low	High	High	High
Interaction	0.96	0.78	0.87	0.60	1.06	0.67
	(2.53)	(2.27)	(2.40)	(1.67)	(3.31)	(2.14)
Pure Firm-Specific News	0.47	0.18	0.05	0.48	0.29	0.53
	(1.79)	(0.71)	(0.22)	(2.29)	(1.34)	(2.32)
Pure 52-week High	0.22	0.23	0.37	0.52	0.08	0.26
	(1.06)	(1.19)	(1.94)	(2.75)	(0.36)	(1.26)
Panel B: Low limits to arbitrage						
	Large	High	High	Low	Low	Low
Interaction	0.16	0.07	0.14	0.24	-0.05	0.00
	(1.02)	(0.38)	(0.51)	(1.09)	(-0.28)	(0.02)
Pure Firm-Specific News	0.05	0.21	-0.08	-0.00	0.35	0.08
	(0.50)	(1.90)	(-0.42)	(-0.03)	(2.24)	(0.85)
Pure 52-week High	0.29	0.15	0.08	-0.07	0.36	0.11
	(2.63)	(1.11)	(0.65)	(-0.54)	(3.86)	(1.07)

Table 9: Return decomposition results: U.S vs Ex-U.S.

This table reports the results of the return decomposition including the interaction effects based on different country subsamples. In Panel A, reports the results of firm located wihtin the U.S. and Panel B of of firms located outside of the U.S. Within each subsample, we sort the firms into country-neutral 5 $\times$ 5 portfolios based on FN and PRC and conduct a return decomposition using the methodology described in Appendix B. Average monthly FFC4 Alpha are the intercepts from time-series regressions of monthly estimates of each effect (e.g., the pure firm-specific news return effect) on the Carhart (1997) four factors. The sample period is from January 2004 to December 2021. FFC4 Alpha in this table is reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	FF4C Alpha			
	U.S.		Ex-U.S.	
	(1)	(2)	(3)	(4)
Interaction	0.61		1.87	
	(2.53)		(4.16)	
Pure Firm-Specific News	0.11	0.54	-0.23	0.78
	(0.64)	(5.54)	(-0.83)	(11.19)
Pure 52-week High	0.13	0.31	0.14	0.71
	(0.70)	(1.66)	(0.63)	(4.82)

Table 10: Return decomposition results: other risk-adjustment methods.

This table reports the return decomposition results using various risk-adjustment methods. In the FF5 column, risk-adjusted returns are estimated from time-series regressions of monthly return components (effects) on Fama and French (2015) five factors. In the FF5C column, we augment FF5 factors with the momentum factor (UMD) by Carhart (1997) in the time-series regression. In the PS column, risk-adjusted returns are estimated from time-series regressions of monthly return components (effects) on Pástor and Stambaugh (2003) four factors. In the FF5+LIQ column, we augment FF5 factors with the liquidity (LIQ) factor by Pástor and Stambaugh (2003) in the time-series regression. In the FF5C+LIQ column, we augment FF5 factors with the liquidity (LIQ) factor by Pástor and Stambaugh (2003) and the momentum factor (UMD) by Carhart (1997) in the time-series regression. The sample period is from January 2004 to December 2021. Alphas in this table are reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	Alpha				
	FF5	FF5C	PS	FF5+LIQ	FF5C+LIQ
	(1)	(2)	(3)	(4)	(5)
Interaction	1.61	1.55	1.53	1.64	1.58
	(5.30)	(5.11)	(4.79)	(5.28)	(5.11)
Pure Firm-Specific News	-0.17	-0.13	-0.17	-0.21	-0.17
	(-0.83)	(-0.66)	(-0.85)	(-0.99)	(-0.82)
Pure 52-week High	0.02	-0.13	0.23	0.05	-0.10
	(0.09)	(-0.72)	(1.21)	(0.24)	(-0.53)

Table 11: Return decomposition results: robustness measures.

This table reports the return decomposition results using different firm-specific news measures. Panel A covers all firms with firm-specific news, Panel B covers firms from the U.S., and Panel C excludes all U.S. firms. In the EAD column, only earnings announcement dates are used to identify firm-specific news. We follow Engelberg et al. (2018) by identifying the earnings announcement day as the day with the highest volume within a the three-day window around the reported announcement day in I/B/E/S. In the $-EAD$ column, we exclude all earnings announcement dates from the firm-specific news measure. In the $t, t+1$ column, we model a slower information diffusion by tagging the next day after news occurrence as a firm-specific news day. In the $+Events$ column, we add further essential events to the firm-specific news measure. Additional events include: partnerships, indexes, marketing, regulatory, permits, exploration, commodity-prices, industrial-accidents, business-operations, credit-default-swap, privacy, ownership. In the $-Macro$ column, we exclude macro-news days. We follow Savor and Wilson (2013) by excluding macro announcement days that have statistically and economically significant impacts on an individual country's market risk premium. In the ϵ column, we extract the idiosyncratic news part from daily returns. We follow Burt and Hrdlicka (2021) by decomposing the daily return into a predictable and idiosyncratic component using the data and asset pricing model from the previous twelve month (t-2 till t-13). Average monthly FFC4 Alpha are the intercepts from time-series regressions of monthly estimates of each effect (e.g., the pure firm-specific news return effect) on the Carhart (1997) four factors. The sample period is from January 2004 to December 2021. FFC4 alpha in this table is reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	FF4C Alpha					
	EAD	$-EAD$	$t, t+1$	$+Events$	$-Macro$	ϵ
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Global						
Interaction	1.21	1.68	1.33	1.22	1.38	1.32
	(1.60)	(5.17)	(4.90)	(3.58)	(3.86)	(4.30)
Pure Firm-Specific News	0.14	-0.37	-0.23	0.02	-0.08	-0.15
	(0.25)	(-2.03)	(-1.51)	(0.10)	(-0.45)	(-0.77)
Pure 52-week High	0.03	0.05	0.21	0.17	0.25	0.11
	(0.16)	(0.24)	(1.31)	(0.95)	(1.47)	(0.65)
Panel B: U.S.						
Interaction	-0.29	0.72	0.52	0.11	0.73	0.87
	(-0.30)	(2.21)	(1.19)	(0.30)	(2.65)	(2.89)
Pure Firm-Specific News	0.84	-0.10	0.01	0.37	0.07	-0.12
	(1.26)	(-0.43)	(0.05)	(1.27)	(0.33)	(-0.55)
Pure 52-week High	0.46	0.14	0.22	0.27	0.13	0.02
	(1.51)	(0.73)	(1.04)	(1.33)	(0.58)	(0.10)
Panel C: Ex-U.S.						
Interaction	1.72	2.21	1.74	1.83	1.81	1.54
	(1.86)	(4.92)	(6.87)	(3.98)	(3.12)	(3.96)
Pure Firm-Specific News	-0.07	-0.48	-0.36	-0.17	-0.11	-0.19
	(-0.10)	(-1.96)	(-2.20)	(-0.61)	(-0.32)	(-0.75)
Pure 52-week High	-0.04	0.03	0.26	0.17	0.34	0.20
	(-0.15)	(0.14)	(1.51)	(0.72)	(1.42)	(0.92)

Table 12: Return decomposition results: placebo test.

This table reports the estimates of the monthly averages for the pure firm-specific news return effect, the pure momentum effect, and the interaction effect. The return decomposition methodology is described in 2.2, and the specifications of the return decomposition are shown in Table 1 and based on the Equation 3 and Equation 4, where we replace $NEAR$ with MOM. The pure firm-specific news effect is computed as $N_{gg} - N_{bb}$, where N_{gg} (N_{bb}) is the return associated with having extremely good (bad) firm-specific news regardless of the stock's momentum. The pure momentum effect is computed as $H_n - H_f$, where H_n (H_f) is the return attributable to having high (low) stock momentum regardless of firm-specific news about the firms. The interaction effect is computed as $I_{gg,n} - I_{bb,f}$, where $I_{gg,n}$ ($I_{bb,f}$) is the return associated with both very good (very bad) firm-specific news and high (low) momentum. Average monthly $CAPM$ alpha, $FF3$ alpha, and $FFC4$ alpha are the intercepts from time-series regressions of monthly estimates of each effect (e.g., the pure firm-specific news return effect) on market excess returns, Fama and French (1993b) three factors, and Carhart (1997) four factors, respectively. The sample period is from January 2004 to December 2021. Alphas in this table are reported in percent. All standard errors are adjusted using Newey and West (1987). t-statistics are in parentheses.

	Alpha					
	CAPM		FF3		FFC4	
	(1)	(2)	(3)	(4)	(5)	(6)
Interaction	-0.12		-0.15		-0.19	
	(-0.42)		(-0.49)		(-0.62)	
Pure Firm-Specific News	0.83	0.81	0.83	0.80	0.82	0.77
	(4.72)	(11.51)	(4.79)	(11.04)	(4.70)	(11.10)
Pure Momentum	0.73	0.68	0.66	0.60	0.46	0.39
	(4.14)	(4.38)	(4.45)	(3.94)	(4.62)	(4.79)

Table 13: Analyst recommendation revision.

This table reports the predictive effects of firm-specific news returns, nearness to the 52-week high, and their interaction on the direction of subsequent analyst recommendation revisions. The analysis is conducted using analyst recommendation revisions on firms with firm-specific news from January 2004 to December 2021. In columns (1–3) of Panel A, we estimate an ordered logit regression model as in Eq. (1), where the dependent the variable takes a value of one when the analyst recommendation revision on a firm is an upgrade, zero when the revision is a reiteration and a negative one when the revision is a downgrade. The independent variable FN is the cumulative firm-specific news returns in the 21 trading days before the recommendation revision days. $NEAR$ is the nearness to the 52-week high of the firm on the trading day before the announcement days. $FN \times NEAR$ is the interaction term between FN and $NEAR$. The control variables are supplier firm characteristics, including analyst dispersion, analyst coverage, standardized unexpected earnings (SUE), market capitalization, book-to-market ratio, past 12-month cumulative returns, idiosyncratic volatility, asset growth, and accruals as of the month-end before the recommendation announcement date. Fama-French 48-industry, year, month, and country fixed effects are included in the regressions. In columns (4–6), we re-perform the above regressions in OLS regressions. Z-statistics in parentheses of columns (1–3) or t-statistics in parentheses of columns (4–6) are computed based on standard errors clustered by firm. In Panel B, the dependent variable is replaced by Upgrade, which is a dummy variable that equals one if the revision is an upgrade and zeroes otherwise. In Panel C, the dependent variable is replaced by Downgrade, which is a dummy variable that equals one if the revision is a downgrade and zeroes otherwise. In Panel B and C, we estimate logit regression models in columns (1–3) and OLS regression models in columns (4–6).

	Ordered Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ***RecChange*** **as the dependent variable**						
FN	0.010	0.030	0.036	0.005	0.013	0.016
	(21.66)	(22.16)	(23.77)	(21.46)	(21.93)	(23.58)
$NEAR$		-0.079	-0.229		-0.064	-0.091
		(-5.74)	(-11.14)		(-8.98)	(-8.47)
$FN \times NEAR$		-0.029	-0.029		-0.013	-0.013
		(-15.13)	(-13.70)		(-14.47)	(-13.25)
Controls	No	No	Yes	No	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	684678	684678	545959	684678	684678	545959
Pseudo/Adj. R^2	0.001	0.001	0.004	0.004	0.004	0.011
Panel B: ***Upgrade*** **as the dependent variable**						
FN	0.009	0.018	0.024	0.002	0.004	0.005
	(19.16)	(12.95)	(15.46)	(18.75)	(12.87)	(15.47)
$NEAR$		-0.142	-0.319		-0.050	-0.068
		(-9.40)	(-13.63)		(-12.80)	(-11.55)
$FN \times NEAR$		-0.011	-0.012		-0.002	-0.003
		(-5.86)	(-5.44)		(-5.48)	(-5.33)
Controls	No	No	Yes	No	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	684678	684678	545959	684678	684678	545959
Pseudo/Adj. R^2	0.001	0.001	0.006	0.007	0.008	0.013

Continued on next page

Table 13 continued

	Ordered Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: *Downgrade* **as the dependent variable**						
FN	-0.011	-0.039	-0.044	-0.003	-0.009	-0.010
	(-21.59)	(-27.28)	(-27.88)	(-21.68)	(-27.42)	(-28.05)
$NEAR$		0.027	0.146		0.014	0.023
		(1.69)	(6.33)		(3.43)	(3.91)
$FN \times NEAR$		0.043	0.042		0.010	0.010
		(21.22)	(19.05)		(20.95)	(18.98)
Controls	No	No	Yes	No	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	684678	684678	545959	684678	684678	545959
Pseudo/Adj. R^2	0.001	0.002	0.007	0.004	0.005	0.011

Appendix A - Decomposition methodology of the 3×3

In the case of a reduced number of stocks, we sort all stocks which experienced a firm-specific news arrival based on their nearness to the 52-week high and their firm-specific news return into two independent country-neutral tercile portfolios. Similar to the main decomposition methodology, we utilize two different Fama and MacBeth (1973) regressions to decompose the returns of the double-sorted portfolios into the two pure effects of firm-specific news and the nearness to the 52-week high as well as the interaction effect of both across the nine portfolios. The regression model, including the interactions, is specified as follows:

$$\begin{aligned} R_{i,t+1} = b_0 &+ b_1 FN^3_{i,t} + b_2 FN^1_{i,t} + b_3 NEAR^3_{i,t} + b_4 NEAR^1_{i,t-1} \\ &+ b_5 FN^3_{i,t} \times NEAR^3_{i,t} + b_6 FN^1_{i,t} \times NEAR^3_{i,t} \\ &+ b_7 FN^3_{i,t} \times NEAR^1_{i,t} + b_8 FN^1_{i,t} \times NEAR^1_{i,t} + \epsilon, \end{aligned} \tag{A.1}$$

where $R_{i,t+1}$ is the stock return of firm i in the next month $t+1$, and right-hand-side variables are dummies indicating the tercile ranking of firm i at the end of the month t for FN and $NEAR$. In the second regression, we exclude the interaction effect from the model:

$$R_{i,t+1} = b_0 + b_1 FN^3_{i,t} + b_2 FN^1_{i,t} + b_3 NEAR^3_{i,t} + b_4 NEAR^1_{i,t-1} + \epsilon \tag{A.2}$$

In Table A.1 we describe how the individual average portfolio return in each of the 3×3 portfolios sorted by the firm-specific news return and the nearness to the 52-week high is decomposed by using the regression parameters and the return components. The lowest nearness to the 52-week high (firm-specific news return) tercile is defined as $NEAR1$ ($FN1$), while the highest nearness to the 52-week high (firm-specific news return) tercile is specified as $NEAR3$ ($FN3$).

[Table A.1 about here.]

In Panel A and Panel B of Table A.1, we present how the different estimated parameters of Equation A.1 and Equation A.2 can be combined to derive the respective average portfolio return in each of the portfolios. In Panel C and Panel D, we further show how the respective portfolio return can be decomposed into four different return components. The return components are the benchmark return (μ), the returns associated with the 52-week high (H), the returns attributable to the firm-specific news (N), and the returns associated with the interaction between the firm-specific news and nearness of the stock price to the 52-week high (I). The first return component reflects the benchmark portfolio. It is the average return of the stocks in the portfolio with neither extreme firm-specific news returns nor an extreme nearness to the 52-week high. The second return component is solely driven by the stocks nearness to the 52-week high, regardless of the firm-specific news return ranking. Sorting the stocks into terciles based on their nearness to the 52-week high results in a return component which is common among the stocks in the same portfolio. Stocks that are far (f) away from the 52-week high are denoted as H_f and are expected to have a negative return, while stocks which are near (n) the 52-week high are denoted as H_n and are expected to have a positive return. To derive the pure 52-week high effect we build a long-short strategy that relies solely on the return predictability of the nearness to the 52-week high. We, therefore, define the pure 52-week high effect as:

$$\text{Pure 52-week High Effect} = H_n - H_f = b_3 - b_4. \tag{A.3}$$

The third return component is solely driven by the firm-specific news return, regardless of the firm-specific news return ranking. Sorting the stocks into terciles based on their firm-specific news return results in a return component that is common among the stocks in the same portfolio. Similiar to Jiang et al. (2021), do positive firm-specific news returns predict higher future stock returns, and therefore the firm-specific news component increases from the $FN1$ tercile to the $FN3$ tercile. Stocks with bad (b) firm-specific news returns are denoted as N_b, whereas good (g) firm-specific news return are denoted as N_g. While bad firm-specific news returns are associated with negative news momentum and therefore expected to have negative returns in the future, are the good firm-specific news return associated with positive future returns. To derive the pure firm-specific news return effect we build a long-short strategy that relies solely on the return predictability of the firm-specific news return. Depending on the assumption that the 52-week high effect moderates the market underreaction to firm-specific news or not we define pure firm-specific news as:

$$\text{Pure Firm-Specific News Effect} = N_g - N_b = (b_1 + b_5) - (b_2 + b_{10}), \text{and} \tag{A.4}$$

$$= b_1 - b_4. \tag{A.5}$$

The fourth and last return component is associated with having, on the one hand, good firm-specific news about the firm and a stock price near the 52-week high and, on the other hand, experiencing bad firm-specific news while having a stock price that is far from the 52-week high.

While the underreaction to the firm-specific news due to the nearness to the 52-week high could also be driven by the less extreme quintiles (e.g., the $FN2$ and $FN4$ quintile) but with a smaller magnitude, we focus our analysis on the most extreme FN and $NEAR$ quintiles. Stocks with extremely bad firm-specific news returns which are far from the 52-week high are denoted as $I_{b,f}$ whereas stocks with extremely good firm-specific news returns that are near the 52-week high are denoted as $I_{g,n}$. Hence, the interaction effect is defined as:

$$\text{Interaction Effect} = I_{g,n} - I_{b,f} = (b_7 - b_{11}) - (b_{14} - b_{10}) \tag{A.6}$$

If investors had a non-distorted belief updating process after the arrival of good (bad) firm-specific news while having a stock price that is near (far) its 52-week high, the interaction effect's long-short strategy would not yield a significant coefficient. In this case, the portfolio returns could still be fully attributable to the single components of the interaction, namely the pure firm-specific news effect and the pure 52-week high effect. On the other hand, if the coefficient of the interaction effect for the long-short strategy is positive and significant, one potential implication is that investors are not willing to update their beliefs and hence are underreacting to the good (bad) news if the stock price is near (far from) its 52-week high.

Table A.1: Specification of return decomposition 3×3

This table describes the specification of the return decomposition as in George et al. (2014) and Huang et al. (2021) by regression parameter and return component for the double-sorted firm portfolios by firm-specific news returns (FN) and nearness to the 52-week high ($NEAR$). To form the double-sorting portfolios we sort each month all firms which experienced firm-specific news arrival into independent and country-neutral 3×3 portfolios based on FN in the previous month and $NEAR$ at the previous month-end. Each cell represents a group of stocks with a particular $NEAR$ and FN ranking. In Panel A (Panel B), we show how the respective portfolio return can be decomposed using the regression parameters from the monthly stock-level Fama and MacBeth (1973) regression as specified in Equation A.1 (Equation A.2). In Panel C (Panel D), we show how the respective portfolio return can be decomposed into different return components. The return components can be disentangled into the benchmark return (μ), the returns associated with the 52-week high (H), the returns attributable to the firm-specific news (N), and the returns associated with the interaction between the firm-specific news and nearness of the stock price to the 52-week high (I). μ reflects the average return of stocks in the portfolio with neither extreme firm-specific news returns nor an extreme nearness to the 52-week high. H reflects the returns associated with being near (n), middle (m), or far (f) from the 52-week high, regardless of the FN ranking. N reflects the returns associated with having good (g) or bad (b) firm-specific news about the firms, regardless of the $NEAR$ ranking. I reflects the returns associated with having both good (bad) firm-specific news about the firm and stock prices near (far from) the 52-week high.

	$FN1$	$FN2$	$FN3$
Panel A: Decomposition by regression parameter *including* the interactions effect			
$NEAR1$	$b_0 + b_2 + b_4$	$b_0 + b_4$	$b_0 + b_1 + b_4 + b_7$
$NEAR2$	$b_0 + b_2$	b_0	$b_0 + b_1$
$NEAR3$	$b_0 + b_2 + b_3 + b_6$	$b_0 + b_3$	$b_0 + b_1 + b_3 + b_5$
Panel B: Decomposition by regression parameter *excluding* the interactions effect			
$NEAR1$	$b_0 + b_2 + b_4$	$b_0 + b_4$	$b_0 + b_1 + b_4$
$NEAR2$	$b_0 + b_2$	b_0	$b_0 + b_1$
$NEAR3$	$b_0 + b_2 + b_3$	$b_0 + b_3$	$b_0 + b_1 + b_3$
Panel C: Decomposition by return component *including* the interactions effect			
$NEAR1$	$\mu + H_f + N_b + I_{b,f}$	$\mu + H_f$	$\mu + H_f + N_g$
$NEAR2$	$\mu + N_b + I_{b,m}$	μ	$\mu + N_g + I_{g,m}$
$NEAR3$	$\mu + H_n + N_b$	$\mu + H_n$	$\mu + H_n + N_g + I_{g,n}$
Panel D: Decomposition by return component *excluding* the interactions effect			
$NEAR1$	$\mu + H_f + N_b$	$\mu + H_f$	$\mu + H_f + N_g$
$NEAR2$	$\mu + N_b$	μ	$\mu + N_g$
$NEAR3$	$\mu + H_n + N_b$	$\mu + H_n$	$\mu + H_n + N_g$

Appendix B - Filter Datastream

Constituent lists

Datastream comprises three types of constituent lists: (1) research lists, (2) Worldscope lists, and (3) dead lists. By using dead lists, we ensure that any survivorship bias is obviated. For each country, we use the union of all available lists and eliminate any duplicates. As a result, one list remains for each country to be used in the subsequent static filter process. Table B.1 provides an overview of the constituent lists for developed markets that are used in this study.

[Table B.1 about here.]

Static screens

I restrict the sample to common equity stocks by applying several static screens, as shown in Table B.2. Screens (1) to (7) are straightforward to apply and common in the literature.

[Table B.2 about here.]

Screen (8) relates to, among others, to work by the following: Ince and Porter (2006), Campbell et al. (2010), Griffin et al. (2010), Karolyi et al. (2012). The authors provide generic filter rules to exclude non-common equity securities from Refinitiv Datastream. we apply the identified keywords and match them with the security names provided by Datastream. A security is excluded from the sample in the event that a keyword coincides with part of the security name. The following three Datastream items store security names and are applied to the keyword filters: 'NAME', 'ENAME', and 'ECNAME'. Table B.3 gives an overview of the keywords used.

[Table B.3 about here.]

In addition, Griffin et al. (2010) introduce specific keywords for individual countries. The keywords are thus applied to the security names of single countries only. For example, German security names are parsed to contain the word 'GENUSSSCHEINE', which declares the security to be a non-common equity. In Table B.4, we give an overview of country-specific keyword deletions conducted in our study.

[Table B.4 about here.]

Dynamic screens

For the securities remaining from the static screens above, we obtained return and market capitalization data from Datastream and accounting data from Worldscope. Several dynamic screens that are common in the literature were installed in order to account for data errors, mainly within return characteristics. The dynamic screens are shown in Table B.5.

[Table B.5 about here.]

Table B.1: Constituent lists developed markets

The table contains the research lists, Worldscope lists and dead lists of developed markets countries in my sample.

Country	List	Country	List	Country	List
Australia	DEADAU	**Hong Kong**	DEADHK	**Spain**	DEADES
	FAUALL		FHKALL		WSCOPEES
	WSCOPEAU		WSCOPEHK		FESALL
Austria	WSCOPEOE	**Ireland**	WSCOPEIR		FSPDOM
	DEADAT		FIEALL		FSPNQ
	FATALL		DEADIE	**Sweden**	WSCOPESD
	FOSTDCT	**Israel**	DEADIL		FSEALL
	FOSTOM		WSCOPEIS		FXSTOALL
Belgium	FBEALL		FILALL		DEADSE
	WSCOPEBG	**Italy**	FITALL	**Switzerland**	WSCOPESW
	DEADBE		DEADIT		FCHALLP
Canada	DEADCA1		WSCOPEIT		DEADCH
	...	**Japan**	WSCOPEJP	**United Kingdom**	DEADGB
	DEADCA6		FJPALL		...
	WSCOPECN		FJPCONS		DEADGB7
	FXTSEALL		FTOKYO		FGBALL
	FCAALL		FXTKSALL		WSCOPEUK
Denmark	FDKALL		DEADJP	**United States**	WSUS1
	WSCOPEDK	**Netherlands**	DEADNL		...
	DEADDK		FNLALL		WSUS26
Finland	FFIALL		WSCOPENL		FUSALL1
	WSCOPEFN	**New Zealand**	WSCOPENZ		...
	DEADFI		FNZALL		FUSALL7
France	DEADFR		DEADNZ		FUSALLA
	WSCOPEFR	**Norway**	DEADNO		...
	FFRALL		FNOALL		FUSALLZ
Germany	DEADDE1		WSCOPENW		DEADUS1
	...	**Portugal**	WSCOPEPT		...
	DEADDE9		FPTALL		DEADUS12
	FGKURS		DEADPT		
	FDEALLP	**Singapore**	DEADSG		
	WSCOPEBD		FSGALL		
			FXSESM		
			WSCOPESG		

Table B.2: Static Screens

The table displays the static screens applied in our study, mainly following Ince and Porter (2006), Schmidt et al. (2017) and Griffin et al. (2010). Column 3 lists the Datastream items involved (on the left of the equals sign) and the values which we set them to in the filter process (to the right of the equals sign). Column 4 indicates the source of the screens.

Nr.	Description	Datastream item(s) involved	Source
(1)	For firms with more than one security, only the one with the biggest market capitalization and liquidity is used.	MAJOR = Y	Schmidt et al. (2017)
(2)	The type of security must be equity.	TYPE = EQ	Ince and Porter (2006)
(3)	Only the primary quotations of a security are analyzed.	ISINID = P	Fong et al. (2017)
(4)	Firms are located in the respective domestic country.	GEOGN = country shortcut	Ince and Porter (2006)
(5)	Securities are listed in the respective domestic country.	GEOLN = country shortcut	Griffin et al. (2010)
(6)	Securities whose quoted currency is different to the one of the associated country are disregarded.[a]	PCUR = currency shortcut of the country	Griffin et al. (2010)
(7)	Securities whose ISIN country code is different to the one of the associated country are disregarded.[b]	GGISN = country shortcut	Annaert et al. (2013)
(8)	Securities whose name fields indicate non-common stock affiliation are disregarded.	NAME, ENAME, ECNAME	Ince and Porter (2006), Campbell et al. (2010), Griffin et al. (2010) and Karolyi et al. (2012)

[a] In this filter rule, the respective pre-euro currencies are also accepted for countries within the euro-zone. Moreover, in Russia 'USD' is accepted as currency, in addition to 'RUB'.
[b] In Hong Kong, ISIN country codes equal to 'BM' or 'KY' and in the Czech Republic ISIN country codes equal to 'CS' are also accepted.

Table B.3: Generic Keyword Deletions

The table reports generic keywords searched for in the names of all stocks of all countries. If a harmful keyword is detected as part of the name of a stock, the respective stock is removed from the sample.

Non-common equity	Keywords
Duplicates	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa
Depository receipts	ADR, GDR
Preferred stock	PF, 'PF', PFD, PREF, PREFERRED, PRF
Warrants	WARR, WARRANT, WARRANTS, WARRT, WTS, WTS2
Debt	%, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT
Unit trusts	.IT, .ITb, TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT
ETFs	AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR
Expired securities	EXPD, EXPIRED, EXPIRY, EXPY
Miscellaneous (mainly taken from Ince and Porter (2006))	ADS, BOND, CAP.SHS, CONV, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD

Table B.4: Country-Specific Keyword Deletions
The table reports country-specific keywords searched for in the names of all stocks of the respective countries. If a harmful keyword is detected as part of the name of a stock, the respective stock is removed from the sample.

Country	Keywords
Australia	PART PAID, RTS DEF, DEF SETT, CDI
Austria	PC, PARTICIPATION CERTIFICATE, GENUSSSCHEINE, GENUSSCHEINE
Belgium	VVPR, CONVERSION, STRIP
Canada	EXCHANGEABLE, SPLIT, SPLITSHARE, VTG\\., SBVTG\\., VOTING, SUB VTG, SERIES
Denmark	\\)CSE\\)
Finland	USE
France	ADP, CI, SICAV, \\)SICAV\\), SICAV-
Germany	GENUSSCHEINE
Israel	P1, 1, 5
Italy	RNC, RP, PRIVILEGIES
Netherlands	CERTIFICATE, CERTIFICATES, CERTIFICATES\\), CERT, CERTS, STK\\.
New Zealand	RTS, RIGHTS
Sweden	CONVERTED INTO, USE, CONVERTED-, CONVERTED - SEE
Switzerland	CONVERTED INTO, CONVERSION, CONVERSION SEE
United Kingdom	PAID, CONVERSION TO, NON VOTING, CONVERSION 'A'

Table B.5: Dynamic Screens

The table displays the dynamic screens applied to the data in our study, following Ince and Porter (2006), Griffin et al. (2010), Jacobs (2016) and Schmidt et al. (2017). Column 3 lists the respective Datastream items. Column 4 refers to the source of the screens.

Nr.	Description	Datastream item(s) involved	Source
(1)	We delete the zero returns at the end of the return time-series that exist because in the case of a delisting, Datastream displays stale prices from the date of delisting until the end of the respective time-series. We also delete the associated market capitalizations.	RI, MV	Ince and Porter (2006)
(2)	We delete the associated returns and market capitalizations in case of abnormal prices (unadjusted prices > 1000000).	RI, MV, UP	The screen originally stems from Schmidt et al. (2017), however we employ it on unadjusted price.
(3)	We delete monthly (daily) returns and the associated market capitalizations if returns exceed 990% (200%).	RI, MV	Griffin et al. (2010); Schmidt et al. (2017)
(4)	We delete monthly returns and the associated market capitalizations in the case of strong return reversals, defined as $(1+r_{t-1})(1+r_t)-1 < 0.5$ given that either r_{t-1} or $r_t \geq 3.0$.	RI, MV	Ince and Porter (2006)
(5)	We delete daily returns and the associated market capitalizations in the case of strong return reversals, defined as $(1+r_{t-1})(1+r_t)-1 < 0.2$ with r_{t-1} or $r_t \geq 1.0$.	RI, MV	Griffin et al. (2010); Jacobs (2016)

Appendix C - Factor construction

We calculate the market factor as the value-weighted returns of all available stocks in excess of the risk-free rate. For the factors value, profitability, investment, and momentum, we estimate the portfolio breakpoints using the country-specific 30% and 70% percentile of the underlying characteristic using only the big-stock sample. In the case of the value stocks, we use the book-to-market ratio to categorize the stocks as Growth (G), Neutral (N), and Value (V). For profitability, we use the cash-based profitability as an underlying characteristic which enables us to sort the stocks into the extreme portfolios Weak (W) and Robust (R). In the case of the investment factor, we base the sorting on the stock's asset growth, which yields a Conservative (C) and Aggressive (A) portfolio. The next factor is based on the stock's momentum and sorts the stocks into the Winner (W) and Loser (L) portfolios. The last factor is based on the stock's Amihud (2002) illiquidity and sorts the stocks into the liquid (AL) and illiquid (AI) portfolios. We follow the size group methodology of Fama and French (2008, 2012, 2017) and assign stocks into three size groups (micro, small, and big) separately for each country and month. Big stocks are defined as the biggest stocks, which together account for 90% of a country's aggregated market capitalization. Small stocks are defined as those stocks that comprise the next 7% of aggregated market capitalization (so that big and small stocks together account for 97% of the aggregated market size of a country). Microcaps comprise the remaining 3%.[14] The final factor calculation is based on the intersection of the different portfolios, while the portfolio returns are value-weighted,

$$\begin{aligned}
SMB &= (SV + SN + SG)/3 - (BV + BN + BG)/3, \\
HML &= (BV + SV)/2 - (BG + SG)/2, \\
RMW &= (BR + SR)/2 - (BW + SW)/2, \\
CMA &= (BC + SC)/2 - (BA + SA)/2, \\
MOM &= (BW + SW)/2 - (BL + SL)/2, \\
LIQ &= (BAL + SAL)/2 - (BAI + SAI)/2.
\end{aligned} \tag{C.1}$$

[14]To distinguish between these size groups, Fama and French (2008) use the 20$^{\text{th}}$ and 50$^{\text{th}}$ percentiles of end-of-June market cap on NYSE stocks as size breakpoints for the U.S. market, which on average are bigger than AMEX or NASDAQ stocks. However, these breakpoints are applied to all (NYSE, AMEX, and NASDAQ) stocks. For international markets, Fama and French (2012, 2017) propose to calculate breakpoints based on aggregated market capitalization, as we do.

Appendix D - Figures and Tables

References

Abdi, F., Ranaldo, A., 2017. A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices. The Review of Financial Studies 30, 4437–4480.

Ali, U., Hirshleifer, D., 2020. Shared analyst coverage: Unifying momentum spillover effects. Journal of Financial Economics 136, 649–675.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Annaert, J., Ceuster, M. D., Verstegen, K., 2013. Are extreme returns priced in the stock market? European evidence. Journal of Banking & Finance 37, 3401–3411.

Ardia, D., Guidotti, E., Kroencke, T. A., 2022. Efficient estimation of bid-ask spreads from open, high, low, and close prices. Working Paper .

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.

Ben-Rephael, A., Da, Z., Israelsen, R. D., 2017. It depends on where you search: Institutional investor attention and underreaction to news. The Review of Financial Studies 30, 3009–3047.

Birru, J., 2013. Psychological Barriers, Expectational Errors, and Underreaction to News. SSRN Electronic Journal .

Brogaard, J., Nguyen, T. H., Putnins, T. J., Wu, E., 2022. What Moves Stock Prices? The Roles of News, Noise, and Information. The Review of Financial Studies 35, 4341–4386.

Burt, A., Hrdlicka, C., 2021. Where Does the Predictability from Sorting on Returns of Economically Linked Firms Come From? Journal of Financial and Quantitative Analysis 56, 2634–2658.

Byun, S.-J., Goh, J., Kim, D.-H., 2020. The role of psychological barriers in lottery-related anomalies. Journal of Banking Finance 114, 105786.

Campbell, C. J., Cowan, A. R., Salotti, V., 2010. Multi-country event-study methods. Journal of Banking & Finance 34, 3078–3090.

Campbell, J. Y., 1991. A Variance Decomposition for Stock Returns. The Economic Journal 101, 157.

Campbell, J. Y., Shiller, R. J., 1988. The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. The Review of Financial Studies 1, 195–228.

Campbell, S. D., Sharpe, S. A., 2009. Anchoring Bias in Consensus Forecasts and Its Effect on Market Prices. Journal of Financial and Quantitative Analysis 44, 369–390.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57–82.

Cen, L., Hilary, G., Wei, K. C. J., 2013. The Role of Anchoring Bias in the Equity Market: Evidence from Analysts' Earnings Forecasts and Stock Returns. Journal of Financial and Quantitative Analysis 48, 47–76.

Chan, W. S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics 70, 223–260.

Chen, L., Da, Z., Zhao, X., 2013. What drives stock price movements? The Review of Financial Studies 26, 841–876.

Coibion, O., Gorodnichenko, Y., 2015. Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts. American Economic Review 105, 2644–2678.

Corwin, S. A., Schultz, P., 2012. A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. The Journal of Finance 67, 719–760.

Da, Z., Liu, Q., Schaumburg, E., 2014. A closer look at the short-term return reversal. Management Science 60, 658–674.

Da, Z., Warachka, M. C., 2009. Cashflow risk, systematic earnings revisions, and the cross-section of stock returns. Journal of Financial Economics 94, 448–468.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor Psychology and Security Market Under- and Overreactions. The Journal of Finance 53, 1839–1885.

Duan, Y., Hu, G., McLean, R. D., 2010. Costly arbitrage and idiosyncratic risk: Evidence from short sellers. Journal of Financial Intermediation 19, 564–579.

Easton, P. D., Monahan, S. J., 2005. An evaluation of accounting-based measures of expected returns. Accounting Review 80, 501–538.

Engelberg, J., McLean, D., Pontiff, J., 2018. Anomalies and News. The Journal of Finance 73, 1971–2001.

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

Fama, E. F., French, K. R., 1993b. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3–56.

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

Fama, E. F., French, K. R., 2012. Size, value, and momentum in international stock returns. Journal of Financial Economics 105, 457–472.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., French, K. R., 2017. International tests of a five-factor asset pricing model. Journal of Financial Economics 123, 441–463.

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

Fong, K. Y. L., Holden, C. W., Trzcinka, C. A., 2017. What are the best liquidity proxies for global research? Review of Finance 21, 1355–1401.

George, T. J., Hwang, C.-Y., 2004. The 52-week high and momentum investing. The Journal of Finance 59, 2145–2176.

George, T. J., Hwang, C.-Y., Li, Y., 2014. Anchoring, the 52-Week High and Post Earnings Announcement Drift. SSRN Electronic Journal .

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

Griffin, J. M., Kelly, P. J., Nardari, F., 2010. Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets. The Review of Financial Studies 23, 3225–3277.

Gutierrez, R. C., Kelly, E. K., 2008. The Long-Lasting Momentum in Weekly Returns. The Journal of Finance 63, 415–447.

Heath, C., Huddart, S., Lang, M., 1999. Psychological Factors and Stock Option Exercise. The Quarterly Journal of Economics 114, 601–627.

Hillert, A., Jacobs, H., Müller, S., 2014. Media makes momentum. The Review of Financial Studies 27, 3467–3501.

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2011. Limited Investor Attention and Stock Market Misreactions to Accounting Information. Review of Asset Pricing Studies 1, 35–73.

Hong, H., Stein, J. C., 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. The Journal of Finance 54, 2143–2184.

Hong, H., Torous, W., Valkanov, R., 2007. Do industries lead stock markets? Journal of Financial Economics 83, 367–396.

Hong, X., Jordan, B. D., Liu, M. H., 2015. Industry information and the 52-week high effect. Pacific-Basin Finance Journal 32, 111–130.

Hou, K., Xue, C., Zhang, L., 2018. Replicating anomalies. The Review of Financial Studies 33, 2019–2133.

Huang, S., Lin, T.-C., Xiang, H., 2021. Psychological barrier and cross-firm return predictability. Journal of Financial Economics 142, 338–356.

Huddart, S., Lang, M., Yetman, M. H., 2009. Volume and Price Patterns Around a Stock's 52-Week Highs and Lows: Theory and Evidence. Management Science 55, 16–31.

Hung, M., Li, X., Wang, S., 2015. Post-Earnings-Announcement Drift in Global Markets: Evidence from an Information Shock. The Review of Financial Studies 28, 1242–1283.

Hung, W., Lin, C.-T., Yang, J. J., 2022. Aggregate 52-week high, limited attention, and time-varying momentum profits. Journal of Banking Finance 141, 106531.

Ince, O. S., Porter, R. B., 2006. Individual equity return data from Thomson Datastream: Handle with care! Journal of Financial Research 29, 463–479.

Jacobs, H., 2016. Market maturity and mispricing. Journal of Financial Economics 122, 270–287.

Jiang, H., Li, S. Z., Wang, H., 2021. Pervasive underreaction: Evidence from high-frequency data. Journal of Financial Economics 141, 573–599.

Jiang, H., Sun, Z., 2014. News and Corporate Bond Liquidity. SSRN Electronic Journal .

Karolyi, A. G., 2016. Home bias, an academic puzzle. Review of Finance 20, 2049–2078.

Karolyi, G. A., Lee, K.-H., van Dijk, M. A., 2012. Understanding commonality in liquidity around the world. Journal of Financial Economics 105, 82–112.

Ke, Z., Kelly, B. T., Xiu, D., 2020. Predicting Returns with Text Data. SSRN Electronic Journal .

Kelley, E. K., Tetlock, P. C., 2017. Retail Short Selling and Stock Prices. The Review of Financial Studies 30, 801–834.

Lam, F. E. C., Wei, K. J., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. Journal of Financial Economics 102, 127–149.

Landis, C., Skouras, S., 2021. Guidelines for asset pricing research using international equity data from Thomson Reuters Datastream. Journal of Banking Finance 130, 106128.

Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. Journal of Accounting and Economics 42, 3–33.

McLean, R. D., 2010. Idiosyncratic Risk, Long-Term Reversal, and Momentum. Journal of Financial and Quantitative Analysis 45, 883–906.

Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements? Journal of Financial Economics 58, 215–260.

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

Newey, W. K., West, K. D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–708.

Pástor, L., Stambaugh, R. F., 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111, 642–685.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80, 563–602.

Pontiff, J., 1996. Costly Arbitrage: Evidence from Closed-End Funds. The Quarterly Journal of Economics 111, 1135–1151.

Pontiff, J., 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics 42, 35–52, conference Issue on Implications of Changing Financial Reporting Standards.

Poteshman, A. M., Serbin, V., 2003. Clearly Irrational Financial Market Behavior: Evidence from the Early Exercise of Exchange Traded Stock Options. The Journal of Finance 58, 37–70.

Roll, R., 1988. R2. The Journal of Finance 43, 541–566.

Savor, P., Wilson, M., 2013. How Much Do Investors Care About Macroeconomic Risk? Evidence from Scheduled Economic Announcements. Journal of Financial and Quantitative Analysis 48, 343–375.

Schmidt, P. S., Von Arx, U., Schrimpf, A., Wagner, A. F., Ziegler, A., 2017. On the construction of common size, value and momentum factors in international stock markets: A guide with applications. Swiss Finance Institute Research Paper 10.

Shleifer, A., Vishny, R. W., 1997. The Limits of Arbitrage. The Journal of Finance 52, 35–55.

Smajlbegovic, E., 2019. Regional economic activity and stock returns. Journal of Financial and Quantitative Analysis 54, 1051—1082.

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

Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. Science 185, 1124–1131.

Vuolteenaho, T., 2002. What drives firm-level stock returns? The Journal of Finance 57, 233–264.

Windmüller, S., 2022. Firm characteristics and global stock returns: A conditional asset pricing model. The Review of Asset Pricing Studies 12, 447–499.

Wurgler, J., Zhuravskaya, E., 2002. Does Arbitrage Flatten Demand Curves for Stocks? The Journal of Business 75, 583–608.

Zhang, X., 2006. Specification tests of international asset pricing models. Journal of International Money and Finance 25, 275–307.